**PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA**

**MINISTRY OF HIGHER EDUCATION AND RESEARCH SCIENTIST**

**Faculty of sciences and technology**

**Electrical Engineering Department**

Title: Thesis Presented for Completion of Academic Master's Degree Requirements

Field: Science and Technology

**Specialization: Communication Systems**

**Under the title:**

# Extracting features for analysis biometric of a face

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***Academic year*: 2023/2024**

# Saber dedications

I dedicate this modest work:

To my very **Dear Parents** for their support throughout my study life and without whom I would never have become

What am I.

**To all** teachers **and** teachers **that I had during** throughout my school career and which allowed me to succeed in my studies.

To my study friends **Amine ,Ala, Mohmmed, Mortdha,Abderrahman.**

See you later **person** who contributed to this work near or far.

# Abbassi dedications

I dedicate this memoir:

To my dear parents for their support and encouragement throughout my years of study and without whom I would never have succeeded and to my family

To all my professors and teachers that I had throughout my school career and who allowed me to succeed in my studies.

To all my friends.

To anyone who has contributed to this work directly or indirectly.

# Thanks

Our thanks and deep gratitude go to our promoter Mr. **Hettiri Messoud** for his supervision, monitoring and advice throughout this period.

Our thanks and gratitude go to the professors and teachers of of communications systems as well as the students and staff encountered throughout our university curriculum.

We would also like to thank the members of the jury for their precious time given to studying our dissertation.

May anyone who has worked directly or indirectly towards the realization of this project through any form of contribution find here the testimony of our deepest gratitude.

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# General Introduction

The international growth of communications, both in volume and diversity (physical travel, financial transactions, access to services, etc.), implies the need to ensure the identity of individuals. Indeed, the importance of the stakes can motivate fraudsters to defeat existing security systems. There is therefore a growing interest in electronic identification and recognition systems. Their common denominator is the need for a simple, convenient, reliable and inexpensive way to verify a person's identity without the assistance of a third party. The access control market has opened up with the proliferation of systems, but none prove effective against fraud, because all use an external identifier such as: badge/card, key, code. It is common to forget an access code. There are also many offices where passwords are noted in lists, which represents a dangerous gap in the company's IT security since all confidentiality is then lost. Likewise, a badge or a key can be , stolen or copied by people with bad intentions. The fault common to all authentication systems is that an object (code, card, etc.) is identified and not the person themselves. Faced with the constraint of authentication by “objects”, biometrics brings simplicity and comfort to users.

This discipline is in fact interested in the analysis of behavior as well as the analysis of human morphology and studies, using mathematical methods (statistics, probabilities, etc.), the biological variations of people. This theme is part of the general problem of biometrics, which is a science which proposes to identify people based on the measurement of their biological indices. Biometrics covers two main approaches: behavioral analysis (signature speed, walking, etc.) or analysis of human morphology (fingerprints, iris, retina, voice, hand, face, etc.). One of the objectives of biometrics is to secure access to premises or equipment. This can be done today by checking an identity document or by entering a password, but both methods of checking are restrictive and can give rise to falsification. The use of biometric techniques must make it possible to identify a person through consultation of a database, or to verify the claimed identity of an individual. We selected the “face” modality because it is a very strong biological index containing numerous indications on the identity of the person and whose image can be acquired in a non-invasive manner. Face shape recognition is the most common and popular technique. It is the most acceptable because it can be used remotely without contact with the object. Using a camera allows you to acquire the shape of an individual's face and then remove certain features. The essential characteristics for face recognition are: eyes, mouth, around the face, tip of the nose, etc. Depending on the system used, the individual must be positioned in front of the camera or may be moving at a certain distance. The biometric data that is obtained is compared to the reference file. The software must be able to identify an individual despite various physical features (mustache, beard, glasses, etc.).

The face is a relatively insecure biometric. Indeed, the acquired signal is subject to much higher variations than other characteristics. These can be caused, among other things, by makeup, the presence or absence of glasses, aging and the expression of emotion. The face recognition method is sensitive to variation in lighting and change in face position during image acquisition.

This dissertation deals with a subject relating to facial authentication. The purpose of an authentication system is to verify the identity of an individual after they have identified themselves. It is therefore not an identification system which is responsible for discovering the a priori unknown identity of an individual.

Several methods have been developed in the literature for face recognition. In our work we opted for two techniques for extracting features from the face image:

- ✓ The first method is Eigenface which is based on principal component analysis. PCA is a mathematical method that can be used to simplify a data set, by reducing its dimension.
- ✓ The second method is the LBP (local Binary Pattern) technique, it is a mathematical method whose principle consists of characterizing the texture of an image by calculating the LBP code for all the image pixels

then calculating the histogram of this LBP image to form a feature vector representing the facial image.

We have chosen to organize our study around four main chapters.

The first chapter is devoted to the general presentation of biometrics. It describes the operating principle of biometric systems then defines the tools used to evaluate their performance. Then, the place of facial recognition among other biometric techniques is analyzed. Through this chapter, we want to position the problem of facial recognition and present its issues and interests compared to others techniques. Finally, we highlight the difficulties encountered by face recognition systems.

In the second chapter, we will discuss the state of the art of face recognition techniques. We are not going to describe all face recognition algorithms but we will focus on the most popular algorithms and those most suited to our study context.

The third chapter is divided into two parts. In the first part we will present the Eigen face algorithm based on principal component analysis, which is a mathematical method that can be used to simplify a dataset, by reducing its dimension, it is used to effectively represent images of faces, which can be approximately reconstructed from a small set of weights and a standard face image. We will see several approaches to improve PCA performance. In the second part we will present the LBP (Local Binary Pattern) approach. It is a mathematical method which based on characterization of image texture by calculating LBP values for each image pixel.

In the fourth chapter, we present the experimental results obtained by each method by analyzing their performances, followed by a discussion with interpretation of the results.

Finally, the general conclusion will summarize the results obtained by the different approaches and give some perspectives on future work.

## I.1 Introduction

A biometric system is essentially a pattern recognition system that uses an individual's biometric data. Biometric systems have been increasingly used in recent years. The appearance of the computer and its ability to process and store data allowed the creation of computerized biometric systems.

In this chapter we will introduce some basic notions and definitions related to biometrics. We will give the operating principle of biometric systems as well as the tools used to measure their performance. We will especially emphasize the place of facial recognition among other biometric techniques, because it constitutes the objective of this theme.

## I.2 Operating modes

Any biometric system can operate in enrollment mode or in verification mode or in identification mode:

- ✓ The mode of **enrollment** is a learning phase which aims to collect biometric information on the people to be identified. Several data acquisition campaigns can be carried out in order to ensure a certain robustness of the recognition system to temporal variations of the data. During this phase, the biometric characteristics of individuals are captured by a biometric sensor, then represented in digital form (signatures), and finally stored in the database. The processing linked to enrollment has no time constraints, since it is carried out “offline”.
- ✓ The mode of **verification or authentication** is a "1 to 1" comparison, in which the system validates a person's identity by comparing the captured biometric data with that person's biometric template stored in the system's database. In such a mode, the system must then answer the following question: “Am I really the person I am proclaiming myself to be?”. Currently verification is carried out via a personal identification number, a user name, or a smart card.
- ✓ The mode **of identification** is a "1 to N" comparison, in which the system recognizes an individual by matching it with one of the models in the database. The person may not be in the database.

## I.3 Structure of a Biometric System

A biometric system is designed using the following four main modules [19], (see Fig. I.1):

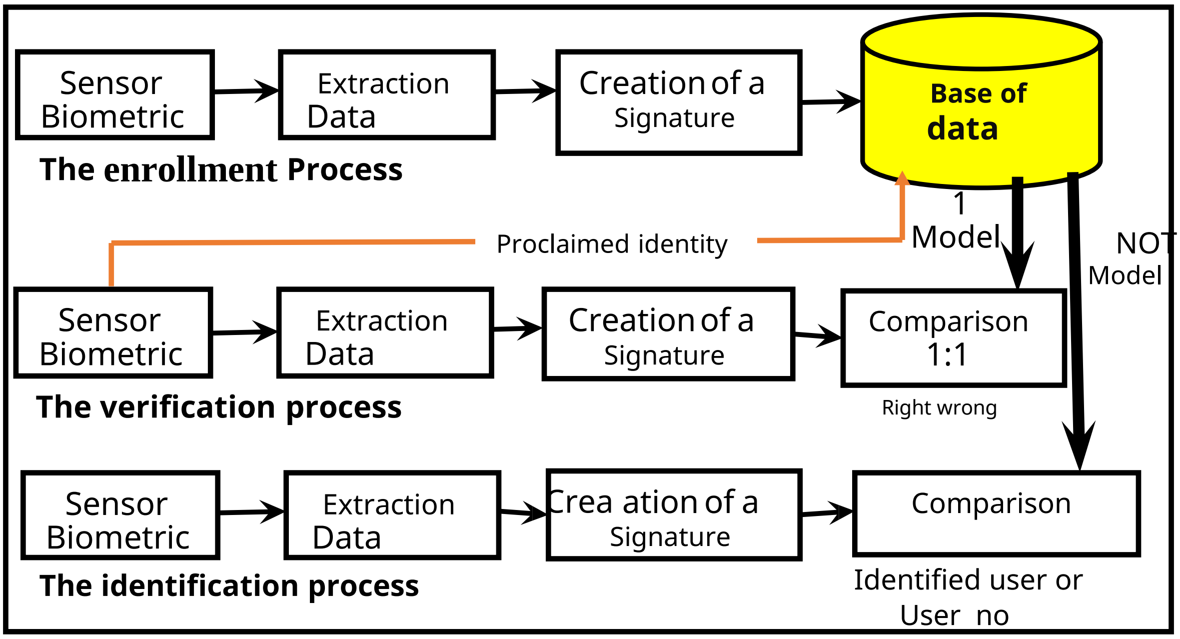


**Fig.I.1:Main modules of a biometric system as well as the different ones.**

The different modules that make up a biometric system are shown in Fig. I.1. Their operation can be summarized as follows:

- Biometric sensor module :corresponds to the reading of certain physiological, behavioral or biological characteristics of a person, by means of a biometric capture terminal (or biometric sensor).
- Data extraction module: extracts relevant information from raw biometric data, for example face images or facial feature regions.
- Signature creation module :creates a digital model to represent the acquired biometric data. This model, also called signature, will be kept on a portable medium (chip or other) or in a database.
- Comparison module :compares the biometric characteristics of a person subject to control (voluntarily or without their knowledge) with the "signatures" stored. This module operates either in verification mode (for a proclaimed identity) or in identification mode (for a sought-after identity).

- Database module :stores biometric templates of enrolled users. The
- registration or registration module :is responsible for registering individuals in the biometric system database. During the enrollment phase, a biometric reader to produce a digital representation of the characteristic first scans an individual's biometric characteristic. Data capture during the registration process may or may not be human-led depending on the application. A quality check is usually performed to ensure that the acquired sample can be safely processed through successive steps.

To facilitate comparison, the input digital representation is further processed by a feature extractor to produce a compact but expressive representation, called a Model or pattern. Depending on the application, the template can be stored in the central database of the biometric system or saved on a Smart card delivered to the user. Generally, models in the database can be updated over time.

## I.4 Biometrics

One of the definitions of biometrics is given by Roethenbaugh [1]: “Biometrics applies to human particularities or characteristics that are unique and measurable, making it possible to automatically recognize or verify identity. ”But No biometric modality is 100% reliable in itself. There are problems, linked to the data capture devices, the user himself or the condition during capture, in which some modality may prove faulty. Among the main physiological and behavioral biometric modalities.

**- Physiological biometrics**

This type is based on the identification of particular physical traits that, for any person, are unique and permanent. This category includes recognition of fingerprints, hand shape, face shape, retina, DNA and iris of the eye.

**- Behavioral biometrics**

This type is based on the analysis of certain behaviors of a person such as the outline of their signature, their gait and their way of typing on a keyboard.

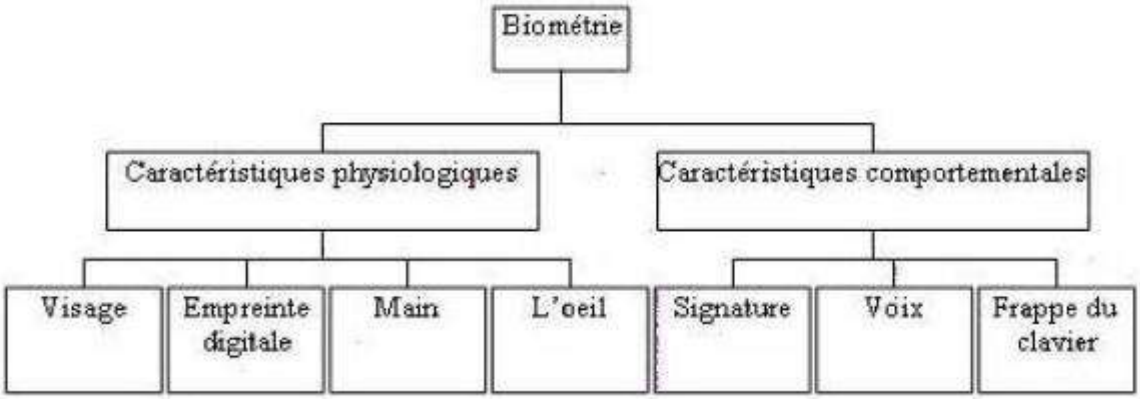


**Fig.I.2:The Classification of Biometrics.**

### I.4.1 Biometric technologies

**Fingerprints :**A fingerprint is made up of a set of locally parallel lines forming a unique pattern for each individual. We distinguish between streaks (or ridges, these are the lines in contact with a surface to the touch) and furrows (these are the hollows between two streaks). The striations contain at their center a set of regularly spaced pores. Each imprint has a set of global (centers and deltas) and local (minutiae) singular points. The centers correspond to places of convergence of the streaks while the deltas correspond to places of divergence. Data acquisition is done by an electronic sensor of optical, thermal, capacitive or ultrasonic type [2].

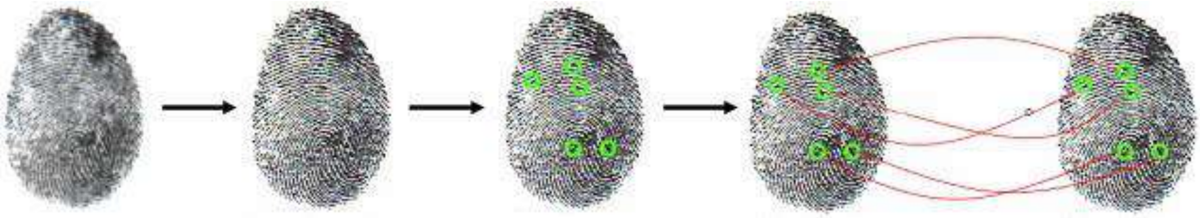

**Fig.I.3:The fingerprint recognition process**.

**The iris :**The iris is an extremely reliable technique because it contains an infinity of characteristic points (fractal set), fraud being nevertheless possible by using lenses. The acquisition of the iris is carried out using a camera to compensate for the inevitable movements of the pupil. It is very sensitive (precision, reflection, etc.) and relatively unpleasant for the user because the eye must remain wide open and it is illuminated by a light source to ensure correct contrast [3][19].

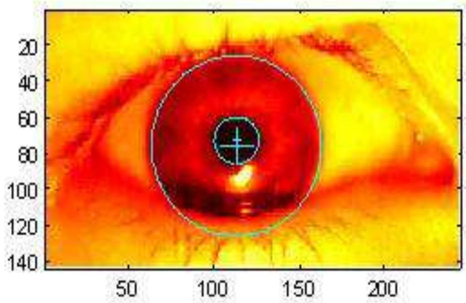


**Fig.I.4:Photo of iris.**

**Hand geometry :**up to 90 characteristics of the hand are measured (shape of the hand and joints, length and width of the fingers, length between joints, etc.). The error rate in recognition is quite high, especially for people belonging to the same family due to a strong resemblance. In addition, the shape of the hand changes significantly with age [5].

**Fig.I.5:Hand geometry recognition device.**

**The retina :**This technique is based on the fact that the blood vessels of a retina are unique for each person. The user must place their eye facing a capture orifice located on the acquisition device. A beam of light passes through the eye to the capillary blood vessels of the retina. The system thus locates and captures approximately 400 reference points. This technique requires close collaboration on the part of the user, as they must place their eye extremely close to the camera.

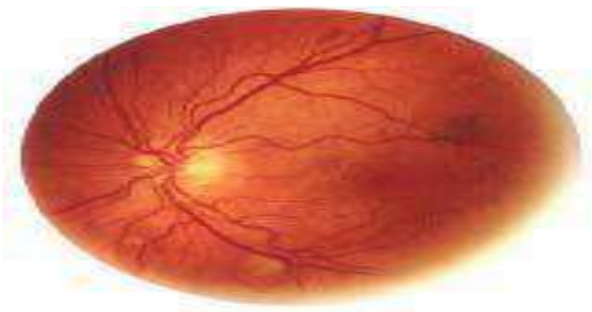

**Fig.I.6:Retina photo.**

**The face :**Several parts of the face (cheeks, eyes, nose, mouth, etc.) are extracted from a photo or video and analyzed geometrically (distance between different points, positions, shapes, etc.). The problem with this method comes from possible disturbances that can transform the face (make-up, low light, presence of a beard or glasses, unusual facial expression, change with age, etc.) [6][7].

Fig.I.7:Capture an image of a face.

**The voice :**The human voice is an interesting biometric characteristic, since it depends on the anatomical structure of the individual as well as the learning of language during childhood. Voice capture is relatively easy to do, using a microphone, but it is susceptible to corruption by ambient noise.

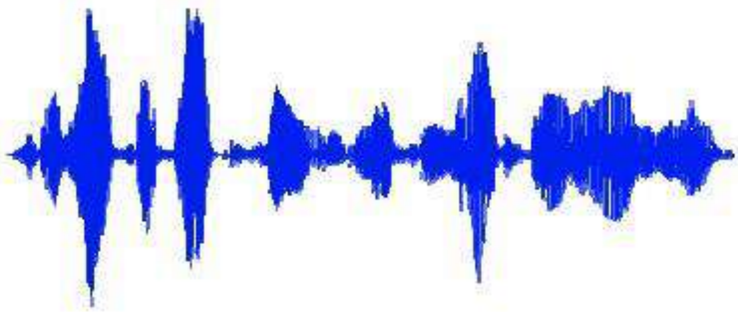

**Fig.I.8:Spectrum of a voice signal.**

**The dynamics of the signature line :**This is a behavioral analysis where different elements (speed measurement, writing order, pressure exerted, acceleration, etc.) are measured during signing. Falsification is possible by going through a learning phase, the signature can decay depending on the stress of the user [9].


**Fig.I.9:Capturing a signature.**

**Keyboard typing dynamics :**A system based on keyboard typing dynamics does not require any special equipment, as each computer has a keyboard. This is a software device that calculates the time a finger is performing a key press and the time a finger is in the air (between keystrokes). This measurement is captured approximately a thousand times per second. The keystroke sequence is predetermined in the form of a password. Initially the user must enter their password a few times so that a reference template is created.

This biometric device is used as a verification method for electronic commerce and as a database access control mechanism [10].

### I.4.2 Evaluation of the performance of biometric systems

Although any physiological or behavioral measure can be used in a biometric recognition system, not all are equally effective. Thus, any good biometric measure must satisfy the following criteria (Jain, Ross and Prabhakar, 2004):

- ✓ Universal: By this we mean that the biometric characteristic must be present for all individuals. For example, it is impossible to collect the fingerprint of an individual who has had their hand amputated or to measure the gait of a quadriplegic person.
- ✓ Distinctive: The measurement carried out on an individual must be sufficiently different from those carried out on other individuals to allow discrimination between them. Here we can think of the genetic code which

varies significantly from one person to another while height is a measurement that several individuals share.

- ✓ Permanent: The fact that the human body ages means that after a certain period of time, a biometric measurement made on an individual can be very different from the initial measurement used for registration in the system. Therefore, it is important to choose a biometric characteristic that remains stable throughout the life of the individual. A good example of this is the pattern present in the iris or even the genetic code of the individual.
- ✓ Easy to measure: This represents how easy it is to collect and quantify biometric measurement. It is easy to record the sound of an individual's voice using a microphone, but it is much less easy to obtain a good quality image of the individuals' retina.
- ✓ Efficient: Efficiency refers to the quantity of resources required to achieve the desired level of quality in the required time. A chemical blood test requires sophisticated equipment and a long period of time to obtain a result compared to collecting an image of an individual's face using a digital camera.
- ✓ Acceptable: This corresponds to the socio-cultural aspects of biometric recognition. Although with the overabundance of security cameras, the normal population no longer cares about having their image collected by multiple systems.
- ✓ Robust: By this we refer to the difficulty of forcing the system to produce an erroneous prediction through the use of a fraudulent technique. The use of makeup techniques for special effects has already made it possible to deceive both humans and machines during facial recognition.

| Biométrie | Universalité | Unicité | Permanence | Mesurabilité | Performance | Acceptabilité | Circonvention |
|---|---|---|---|---|---|---|---|
| DNA | Haute | Haute | Haute | Faible | Haute | Faible | Faible |
| Oreille | Moyenne | Moyenne | Haute | Moyenne | Moyenne | Haute | Moyenne |
| Visage | Haute | Faible | Moyenne | Haute | Faible | Haute | Haute |
| Thermo Visage | Haute | Haute | Faible | Haute | Moyenne | Haute | Haute |
| Empreinte | Moyenne | Haute | Haute | Moyenne | Haute | Moyenne | Moyenne |
| Démarche | Moyenne | Faible | Faible | Haute | Faible | Haute | Moyenne |
| Géométrie Main | Moyenne | Moyenne | Moyenne | Haute | Moyenne | Moyenne | Moyenne |
| Veines Main | Moyenne | Moyenne | Moyenne | Moyenne | Moyenne | Moyenne | Faible |
| Iris | Haute | Haute | Haute | Moyenne | Haute | Faible | Faible |
| Frappe Clavier | Faible | Faible | Faible | Moyenne | Faible | Moyenne | Moyenne |
| Odeur | Haute | Haute | Haute | Faible | Faible | Moyenne | Faible |
| Rétine | Haute | Haute | Moyenne | Faible | Haute | Faible | Faible |
| Signature | Faible | Faible | Faible | Haute | Faible | Haute | Haute |
| Voix | Moyenne | Faible | Faible | Moyenne | Faible | Haute | Haute |

**Fig.I.10:Comparison between biometric techniques [11].**

### I.4.3 Applications of biometric systems

Biometrics applications can be divided into three main groups:

- **Commercial applications :**such as computer network opening, electronic data security, e-commerce, Internet access, credit card, physical access control, cellular telephone, medical records management, distance study, etc.
- **Government applications :**such as national ID card, driving license, social security, border control, passport control, etc.
- **Legal applications :**such as body identification, criminal search, terrorist identification, etc.

Nowadays biometric systems are increasingly used in civilian applications. For example, the **Schiphol Privium** device at Amsterdam Airport uses an iris sensor to speed up the passport and visa control procedure [12]. Passengers insert their card into a reader and face a camera, the latter acquires the image of the eye. Image processing processes are then launched in order to locate the iris and calculate a signature called “Iris code”[13]. Once the Iris code has been calculated, it is compared to the data stored in the card to identify the passenger. A similar device is also used to verify the identity of airport employees who work in high security areas.

### I.4.4 Measuring the performance of a biometric system

First of all, in order to understand how to determine the performance of a biometric system, we need to clearly define three main criteria.

1. The first criterion is called the **false rejection rate** (“**F**alse **R**eject **R**ate” or **FRR**). This rate represents the percentage of people who are supposed to be recognized but who are rejected by the system.

$$\mathrm{FRR} = \frac{\text{number of rejected clients (FR)}}{\text{total number of client accesses}}$$

Such as FR false rejection is when the system rejects a legitimate client.

2. The second criterion is the **false acceptance rate** (“**F**alse **Accept R**ate” or **FAR**).This rate represents the percentage of people who are not supposed to be recognized but who are still accepted by the system.

$$\mathrm{FAR} = \frac{\text{number of accepted impostors (FA)}}{\text{total number of impostor accesses}}$$

Such as F.A. corresponds to the case where the system accepts an individual who has proclaimed an identity that is not their own.

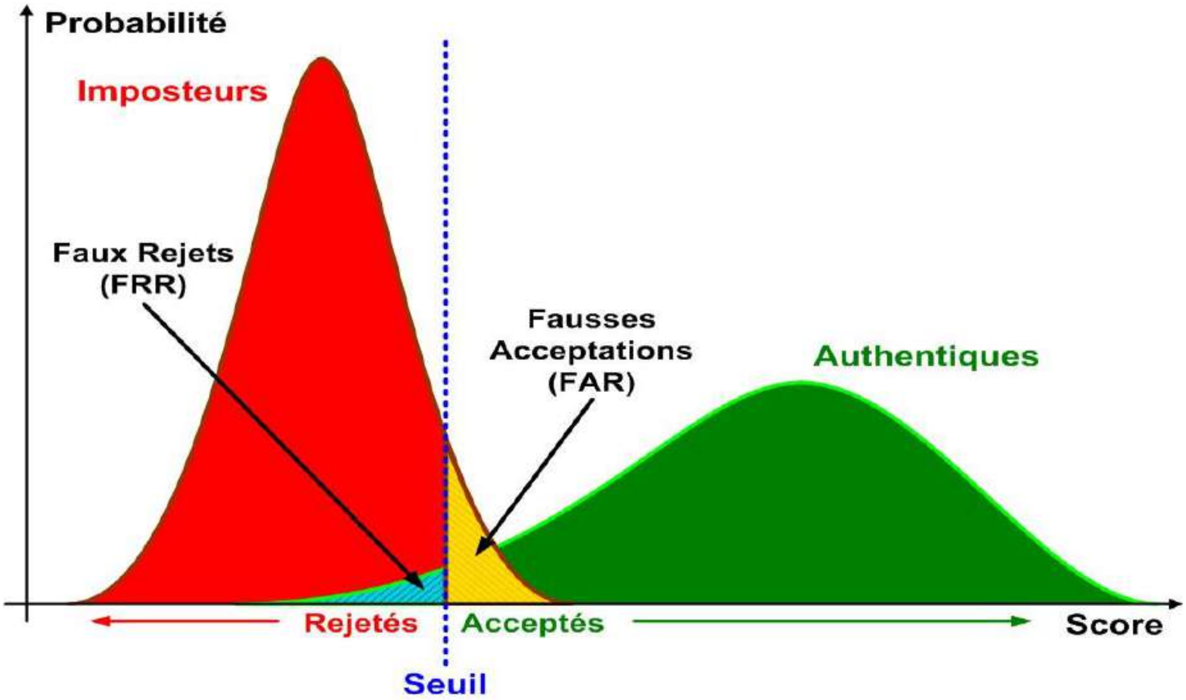


**Fig.I.11:Illustration of the FRR and the FAR.**

3. The third criterion is known as **equal error rate**(“**E**quality **E**rror **R**ate” or **EER**). This rate is calculated from the first two criteria and constitutes a common performance measurement point. This point corresponds to where FRR = FAR, i.e. the best compromise between false rejections and false acceptances.

## I.5 Face recognition

Given the growing demand for surveillance and access control of public places such as airports, banks and administrations, facial recognition has attracted great interest among the scientific community.

If for a human being, recognizing a face is a natural and easy action, it is quite different for an autonomous biometric system. For a computer, such an operation is instead based on a complex processing chain, based on complex algorithms.

Face recognition systems are based on image analysis algorithms that can identify people associated with them. These programs create an image of the face, measuring its characteristics. They then produce an individual file, called a “Template or signature”. The Templates are then compared with all existing images in the database, resulting in a similarity score.

Typical sources of images used in face recognition include video cameras and digital still cameras. It then involves detecting the presence of a face in the image using artificial intelligence techniques. Face detection is a very broad area and will not be the subject of our study.

Furthermore, we can classify face recognition systems into two main categories depending on the source of image capture: face recognition in a video sequence or from still images. In the latter case, we can also differentiate systems based on 3D images [16] from those using 2D images.
We will mainly focus on face recognition systems based on fixed 2D images through image databases built and shared by research laboratories specializing in this field.

### I.5.1 Motivation: (why face recognition?)

Over the last twenty years, automatic face recognition has become a primordial issue, particularly in the fields of indexing multimedia documents and especially in security, this is due to the needs of today's world but also to its advantageous characteristics which we can quote:

- The availability of acquisition equipment, their simplicity and low costs.
- System passivity: A face recognition system does not require any cooperation from the individual, such as placing a finger or hand on a specific device or speaking into a microphone. In fact, the person only has to stay or walk in front of a camera so that they can be identified by the system.

In addition, this technique is very effective for non-standard situations, i.e. cases where we cannot have the cooperation of the individual to be identified, for example during an arrest of criminals. Of course, face recognition is not the most reliable compared to other biometric techniques, but it can be so if we use more effective approaches in addition to the right choice of identification characteristics representing the face in question.

## I.6 Classes of face recognition techniques

### I.6.1 Global methods

The overall methods are based on well-known statistical analysis techniques. It is not necessary to identify certain characteristic points of the face (such as eye centers, mouth centers, etc.) apart to normalize the images. In these methods, face images (which can be seen as matrices of pixel values) are processed globally and are usually transformed into vectors, which are easier to manipulate.

The main advantage of global methods is that they are relatively quick to implement and the basic calculations are of medium complexity. On the other hand, they are very sensitive to variations in lighting, pose and facial expression. This is easily understood since the slightest variation in environmental conditions leads to inevitable changes in the values of the pixels which are processed directly.

These methods mainly use face subspace analysis. This expression is based on a relatively simple fact: a class of "shapes" which interests us (in our case,the faces) resides in a subspace of the input image space. Thus, the representation of the original image is very redundant and the dimensionality of this representation could be greatly reduced if we focus only on the shapes that interest us. The use of subspace modeling techniques has advanced facial recognition technology significantly.

We can distinguish two types of techniques among global methods, linear techniques and nonlinear techniques.

Among the most well-known global methods there are: PCA, LDA/FLD, etc.

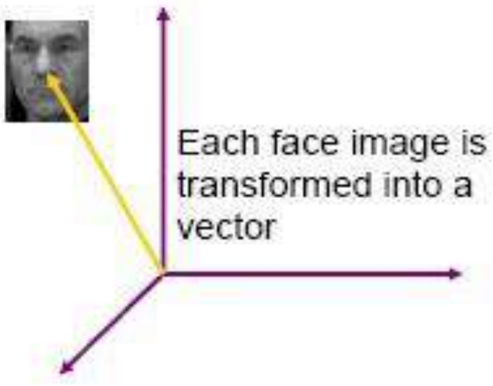


**Fig.I.12:the principle of global methods.**

### I.6.2 Local methods

Local methods, based on models, use a priori knowledge that we have about the morphology of the face and are generally based on characteristic points of it. **Kanade** presented one of the first algorithms of this type [17] by detecting certain points or characteristic features of a face then comparing them with parameters extracted from other faces. These methods provide another approach to account for nonlinearity by constructing a local feature space and using appropriate image filters, such that face distributions are less affected by various changes.

All of these methods have the advantage of being able to more easily model variations in pose, lighting and expression compared to global methods. However, they are more cumbersome to use since it is often necessary to manually place a fairly large number of points on the face while global methods only require knowing the position of the eyes in order to normalize the images, which can be done automatically. and quite reliably by a detection algorithm [18].

In this category, we find several methods such as: gabor filters, Dynamic link architecture, HMM…

### I.6.3 Hybrid methods

Hybrid methods combine the advantages of global methods and by combining the detection of geometric (or structural) characteristics with the extraction of local appearance characteristics.

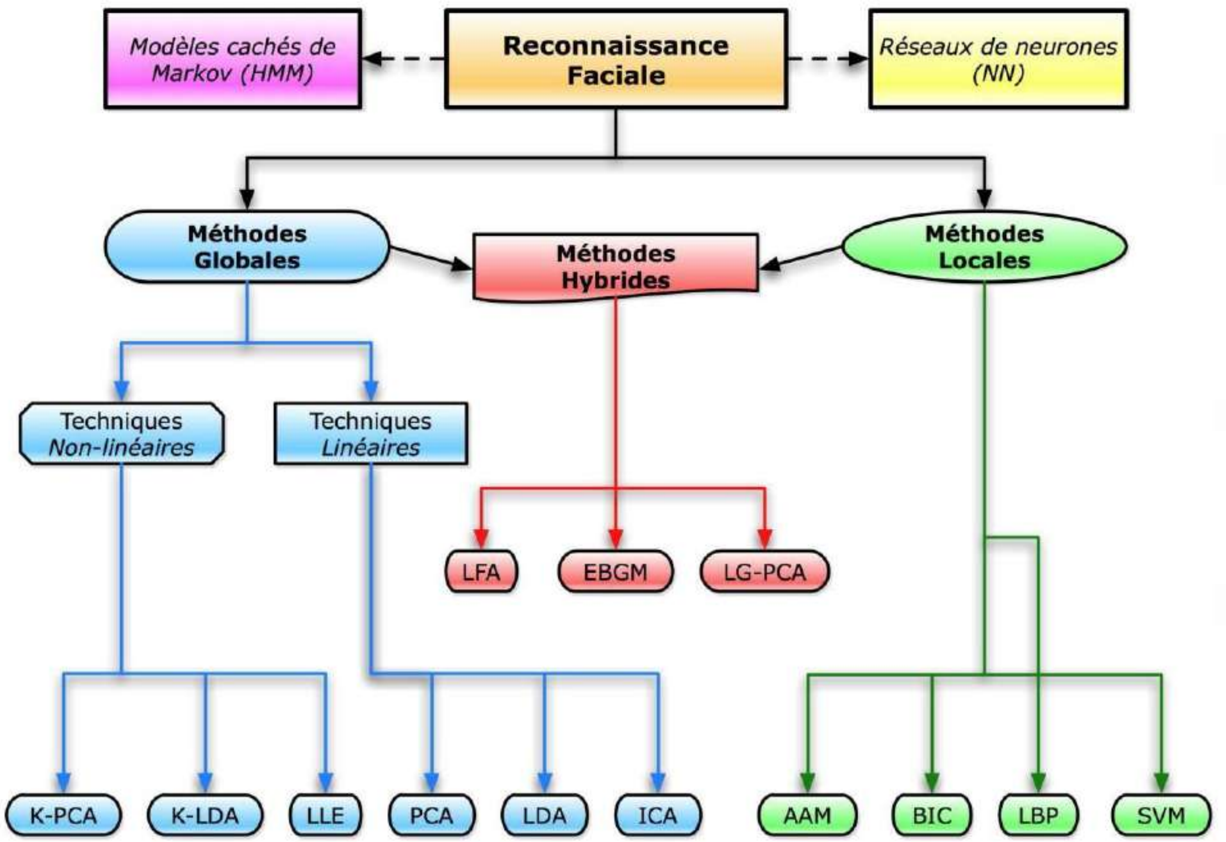


**Fig.I.13:A classification of the main algorithms used in facial recognition.**

## I.7 Face recognition systems

The recognition system uses the facial characteristics thus extracted to create a digital signature, which it stores in a database. Thus, each face in the database is associated with a unique signature, which characterizes the corresponding person. Recognition of a query face is obtained by extracting the corresponding query signature and matching it with the closest signature in the database. Recognition depends on the method of comparison used: verification or identification. The recognition systems can be represented by the following figure:

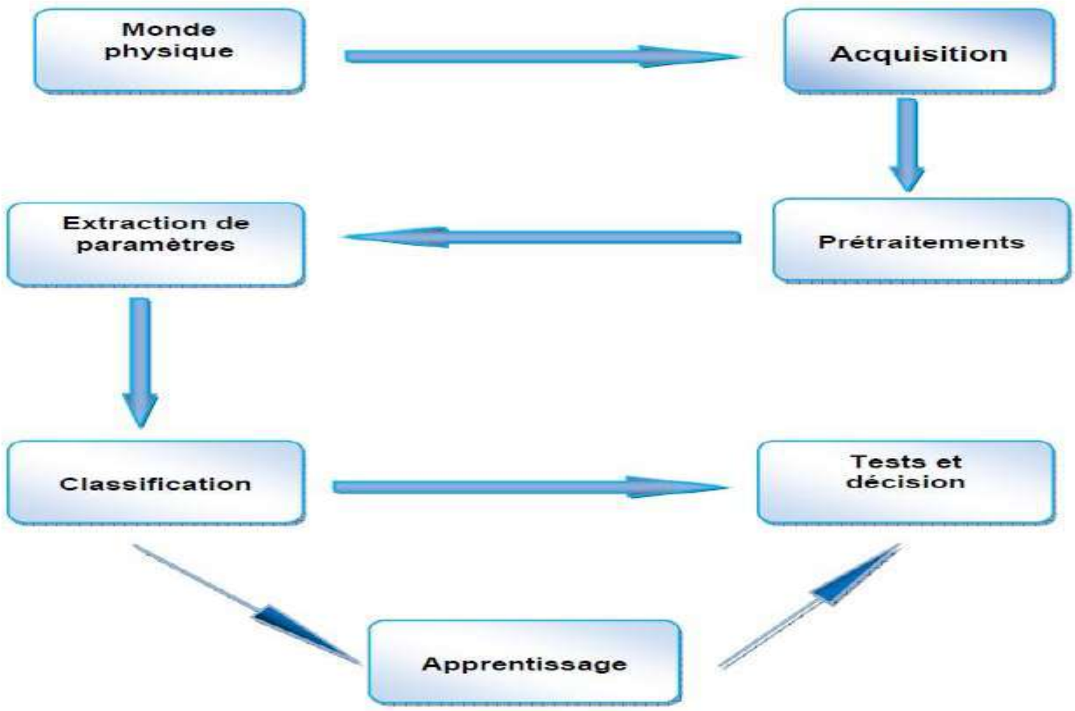


**Fig.I.14:Recognition system.**

So to be identified, the image of a person in a face recognition system follows the following steps:

### I.7.1 The physical world (The exterior)

This is the real world outside the system before image acquisition. In this step, we generally take into account three essential parameters: Lighting, posture variation and scale. The variation of one of these three parameters can lead to a distance between two images of the same individual greater than that separating two images of two different individuals, and consequently a false identification.

### I.7.2 Image acquisition

This step involves extracting the user's image from the outside world in a static state using a camera or dynamic using a camera. Afterwards, the extracted image will be digitalized which gives rise to a two-dimensional representation of the face, characterized by a gray level matrix. The image in this step is in a raw state which creates a risk of noise which can degrade system performance.

### I.7.3 Pretreatments

The role of this step is to eliminate the parasites caused by the quality of the optical or electronic devices during the acquisition of the input image, with the aim of not keep only the essential information and therefore prepare the image for the next step. It is essential because we can never have an image without noise because of the background and the light which is generally unknown. There are several types of image quality processing and improvement, such as: normalization, equalization and median filter. This step can also contain the detection and localization of the face in an image, especially where the decor is very complex.

### I.7.4 Parameter extraction

In addition to classification, the parameter extraction step represents the heart of the recognition system; it consists of carrying out image processing in another simpler workspace which ensures better use of data, and therefore allow the use, only, of useful, discriminating and non-redundant information.

### I.7.5 Classification (Modeling)

This step consists of modeling the parameters extracted from a face or a set of faces of an individual based on their common characteristics. A model is a set of useful, discriminative and non-redundant information which characterizes one or more individuals having similarities.

### I.7.6 Learning

This is the stage where we make individuals learn the system, it consists of memorizing the parameters, after extraction and classification, in a well-ordered database to facilitate the recognition phase and decision-making, it is in a way the memory of the system.

### I.7.7 The decision

This is the step that makes the difference between an individual identification system and a verification system. In this step, an identification system consists of finding the model that best matches the face taken as input from those stored in the database, it is characterized by its recognition rate. On the other hand, in a verification system it is a question of deciding whether the input face is indeed that of the proclaimed individual (model) or it is an impostor, it is characterized by its EER (equal error rate ).

## I.8 Main difficulties in face recognition

For the human brain, the process of recognizing faces is a high-level visual task. Although humans can detect and identify faces in a scene without much difficulty, building an automatic system that accomplishes such tasks represents a serious challenge. This challenge is all the greater when the image acquisition conditions vary greatly. There are two types of variations associated with facial images: inter- and intra subject. Inter-subject variation is limited because of the physical resemblance between individuals. On the other hand, the intra-subject variation is wider. It can be attributed to several factors which we analyze below.

### I.8.1 Change of illumination

Lighting variations make the face recognition task very difficult. Indeed, the change in appearance of a face due to illumination sometimes turns out to be more critical than the physical difference between individuals, and can lead to misclassification of the input images.

**Fig.I.15:Example of lighting variation.**

### I.8.2Variation of pose

The face recognition rate drops considerably when pose variations are present in the images. Pose variation is considered a major problem for facial recognition systems. When the face is in profile in the image plane (orientation < 30°), it can be normalized by detecting at least two facial features (passing through the eyes). However, when the rotation is greater than 30°, geometric normalization is no longer possible.

**Fig.I.16:Examples of pose variations.**

### I.8.3 Facial expressions

Facial deformation which is due to facial expressions is located mainly on the lower part of the face. The facial information located in the upper part of the face remains almost invariable. It is generally sufficient to make an identification. However, given that facial expression modifies the appearance of the face, it necessarily leads to a reduction in the recognition rate. Face identification with facial expression is a challenging problem that is still relevant and remains unsolved.

**Fig.I.17:Examples of variation of expressions.**

### I.8.4 Presence or absence of structural components

The presence of structural components such as the beard, the mustache, or the Glasses can dramatically alter facial characteristics such as shape, color, or size of the face. In addition, these components can hide basic facial characteristics, thus causing a failure of the recognition system.

### I.8.5 Identical twins

Who have the same DNA code can mislead people who do not know them (people familiar with twins have received a large amount of information about them and are therefore much more qualified to distinguish twins.). It is unlikely that automatic face verification will ever be able to detect the very subtle differences that exist between twins.

## I.9 Conclusion

In this chapter, we presented the technologies used in biometric systems for person identification. We also gave an overview of the techniques for measuring their performance. This study allowed us to note that face recognition is attracting more and more interest from the scientific community, because it presents several challenges and technological obstacles. Finally, we highlighted the various difficulties inherent in automatic face recognition, which allowed us to clearly define the issues addressed in this dissertation. The techniques used at the different stages of face recognition are detailed in the following chapter.

## II.1 Introduction

Although there are many face recognition algorithms that work well in constrained environments. Various image changes present a great challenge to a recognition system that must be robust with respect to large variabilities in facial images such as facial expressions, facial pose, and lighting. To deal with this problem, it is important to choose an appropriate representation of facial images. This representation must be compact and meaningful.

The aim of this chapter is to provide an overview of the most significant methods in face recognition.

## II.2 Principal Component Analysis

The PCA algorithm was born from the work of MA. Turk and A.P. Pentland at the MIT Media Lab, in 1991[19,20].

The main idea consists of expressing the M initial images according to a basis of particular orthogonal vectors "eigenvectors" containing independent information from one vector to another. These new data are therefore expressed in a way more appropriate for face recognition. The goal is to extract feature information from a face image using KLT or DCT, to encode it as efficiently as possible in order to compare it to a database of similarly encoded models [20]. .In mathematical terms, this amounts to finding the eigenvectors of the covariance matrix formed by the different images in our learning base. Therefore, PCA does not require any a priori knowledge about the image and proves to be more effective when coupled with the Mah Cosine distance measurement, but its simplicity to implement contrasts with a high sensitivity to changes in illumination, pose and facial expression [21].

There are several methods based on the PCA technique such as the “Eigen face” method. Its principle is as follows: given a set of images of example faces, the first step is to find the main components of these faces. This amounts to determining the eigenvectors of the covariance matrix formed by all the example images. Each example face can then be described by a linear combination of these eigenvectors. To construct the covariance matrix, each face image is transformed into a vector. Each element of the vector corresponds to the light intensity of a pixel.

In [22], the authors demonstrated that the covariance matrix C can be written: $C = CI + C£$

That is, it is equal to the sum of the intra-person dispersion matrix $C$ and the inter-person dispersion matrix $C£$. In the case of a single learning example per person, $CI = 0$, and therefore the equation reduces to $C£$.

The Eigen space estimated from the matrix $C£$ only is unreliable, because it cannot effectively differentiate between of identification other errors due to transformation and noise [22]. To illustrate the influence of the number of training examples per person on recognition performance, the authors used the ORL database [23] as a test base. The ORL database contains images of 40 individuals, each recorded in 10 different views. In their experiment, the authors fixed the number of test faces. On the other hand, they varied the number of learning faces. Thus, for each person, they used the last image (Figure II.1) for the test and randomly chose the first n images (n <= 9) for training. This procedure was repeated twenty times.

**Fig.II.1:The ten views of a person in the ORL database.**

In the extreme case, if only one training example per person is used, the average identification rate for Eigen face falls below 65%. This rate reaches 95% when we use nine learning examples per person.

### II.3 Linear Discriminant Analysis (LDA)

The LDA algorithm was born from the work of Belhumour et al. From Yale University (USA), in 1997[24]. It is also known as “Fisher faces”. Unlike the PCA algorithm, the LDA algorithm performs real class separation. To be able to use it, you must first organize the image learning base into several classes: one class per person and several images per class. LDA analyzes the eigenvectors of the data dispersion matrix, with the objective of maximizing variations between images of different individuals (interclasses) while minimizing variations between images of the same individual (intra-classes).

However, when the number of individuals to be processed is lower than the resolution of the image, it is difficult to apply LDA which can then reveal singular (noninvertible) dispersion matrices.

As PCA does not take into account class discrimination but LDA solves this problem, and standard LDA-based methods such as Fisher faces, first apply PCA for dimension reduction and then discriminant analysis. Appropriate questions about PCA are usually related to the number of principal components (PCs) used and how they affect performance. Concerning discriminant analysis one must understand the reasons for over-fitting and how to avoid it. The answers to these two questions are closely linked. It can actually be shown that using more CPs can lead to a decrease in authentication performance. The explanation of this behavior is that the CPs corresponding to the vectors which have small eigenvalues correspond to the high frequency components usually encode the noise. As a result, if the eigenvectors corresponding to small eigenvalues are used to define the reduced PCA subspace, the FLD process is also accompanied by noise and consequently over-fitting takes place. For this reason the Enhanced FLD Model (EFM) is used to overcome these problems associated with over-fitting, shown in detail below.

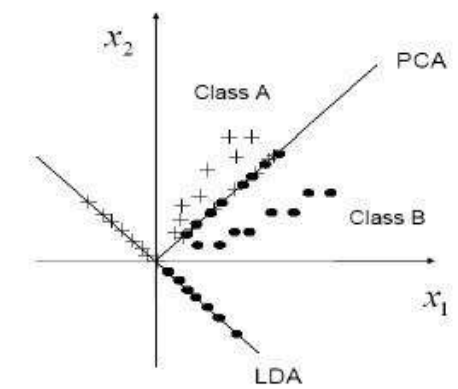


**Fig.II.2:PCA and LDA projections of a dataset.**

## II.4 Independent component analysis

Independent component analysis (ICA) was introduced by signal processing specialists to find a solution to the source separation problem when the mixture function F is unknown. The processing consists of extracting the linear components of a multivariate observation so that they are also independent as possible. In addition to signal processing, this technique has been used in other fields, namely telecommunications and biomedical signal processing. It is generally used to analyze signals from multiple sensors for which the exact nature of the sources is unknown, hence its name blind source separation [27].

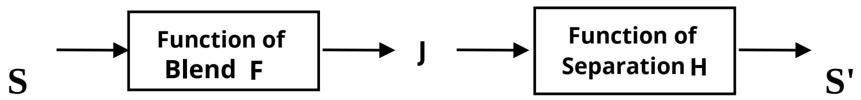


**Fig.II.3:General model of source mixing and separation.**

In the case considered in face recognition, the separation function H makes it possible to obtain an estimate **S'** signing an image **J** according to **S'= H(J)**. To determine the function H, as for the PCA, we start from the covariance matrix C of the images. Then, rather than diagonalizing this matrix as in PCA, we seek to factor it in a form which allows the axes around which the information is concentrated to not necessarily be orthogonal [28, 29]. This factorization, obtained iteratively by various algorithms, jointly determines the separation function H.

This approach was used by [30] for face recognition. It proposes two different models of source mixing leading to the formation of image J from the signatures (Fig.II.4). In each case, it uses independent component analysis to determine the separation functions. Both methods were tested on the FERET database and gave good results (88% recognition rate). The tests carried out on the Yale Faces and AT&T databases also gave satisfactory results (respectively 96.36% and 99.00% recognition rate) and thus proved the effectiveness of the method [31].

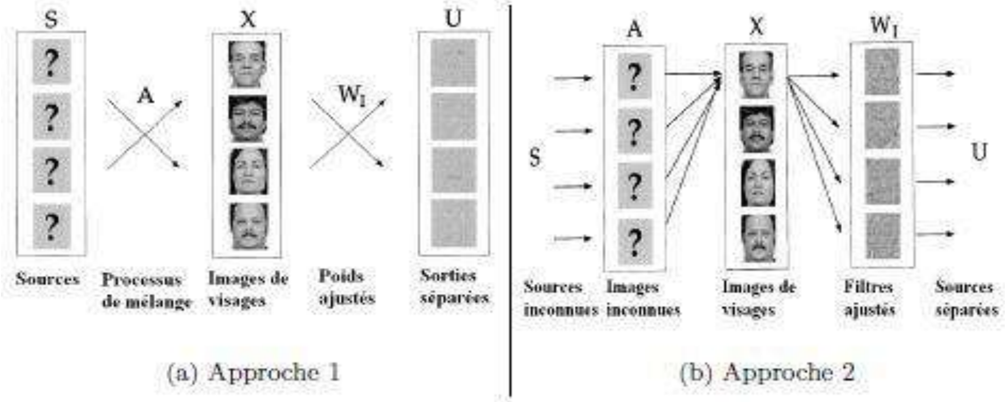


**Fig.II.4:The image synthesis model of the ICA architecture.**

It should also be noted that many variations of the ACI algorithm have been proposed recently. We find in particular the rapid technique (Fast ICA), or also FICA (FLD ICA): the combination between independent component analysis and Fisher's discriminant analysis [32]. These improvements made it possible to remedy the problem of calculation time observed with classic ACI. There are also variations based on how the original image is processed, such as the block-based ACI technique [33]. This involves subdividing the image into a set of blocks and applying an ACI to each. In terms of comparison, it has been demonstrated that the ACI, as well as its different variants, performs very well compared to the PCA. Indeed, the components sought in the image representation space are not necessarily orthogonal for the ACI, whereas they are for the PCA.

## II.5 Neural networks (ANN)

Among the non-linear signature extraction techniques that have been widely used for face recognition are those that rely on an artificial neural network (ANN). These were initially inspired by the physiology of the nervous system so perfectly created and designed. The formal neuron, introduced by J. McCulloch and W. Pitts in the 1940s, constitutes the basis of the architecture of ANNs.

A formal neuron is a non-linear algebraic function (parameterized and with bounded values) of real variables called inputs, which attempts to reproduce this mode of operation. A formal neuron performs a weighted sum of the input signals that reach it. This weighted sum serves as a parameter for a function, often non-linear, which transforms it into a new signal transmitted to the output (Fig.II.5).

With reference to the functioning of the biological neuron, the function occurring after the summation of the inputs is called activation function.

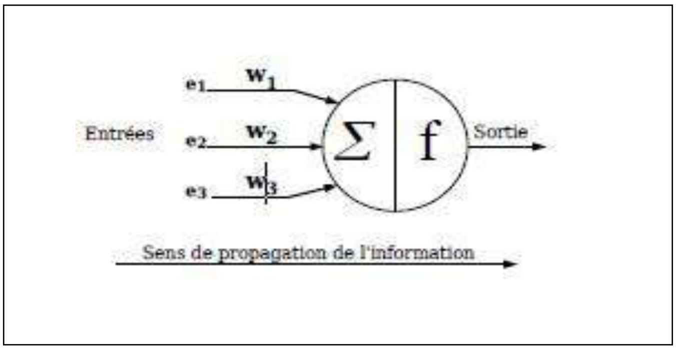


**Fig.II.5:Formal neuron**.

ANNs have been used in many applications, particularly for data classification, complex process modeling and nonlinear signal processing. This research has generated a range of network architectures, each of which responds perfectly to a given application. We note in particular the MLP (Multi-Layer Perceptron, Multilayer Perceptron), the RBF (Radial Basis Function) architecture and the SOM (Self Organizing Maps, Kohonen).

In the case of face recognition, we see that neural networks have been used in all the modules involved in the processing chain. They are used for face detection, signature extraction and classification.

## II.6 Support Vector Machine (SVM)

It is a technique which was proposed by V.Vapnik in 1995, it is used in several statistical fields (classification, regression, fusion, etc.).

The essential idea of this approach consists of projecting the data from the input space (belonging to different classes) which are non-linearly separable, into a higher dimensional space called feature space, so that the data becomes linearly separable [25,26].

In this space, the optimal hyperplane construction technique is used to calculate the classification function separating classes such as:

- Vectors belonging to different classes are on different sides of the hyperplane.

- The smallest distance between the vectors and the hyperplane (the margin) is maximum.

Since its introduction in the field of pattern recognition, several works have shown the effectiveness of this technique, mainly in image processing.

**II.7 Hidden Markov model**

Hidden Markov models HMMs are widely used in pattern recognition, artificial intelligence and even natural language processing. THE HMMs are generally used for the statistical modeling of non-stationary time vector series. By considering facial information as a sequence varying over time, the HMM can be applied to face recognition [35]. The most significant facial features in a frontal face image, namely hair, forehead, eyes, nose and mouth, appear in a natural order from top to bottom. low, even in the case where there are small rotations. Based on this observation, the image of a face can be modeled using a HMM unidimensional by assigning a state to each of these regions. THE HMM classifies a characteristic by the property of the Markov chain. A sequence of pixel values forms a Markov chain, if the probability that the system at time n+1 is in state x n+1 depends only on the probability that the system at time n is in state x n.

In Markov chain, the transition from one state to another is probabilistic which gives a probability distribution of all the outputs of each state. This result is used to make the comparison between two faces [35] [36].

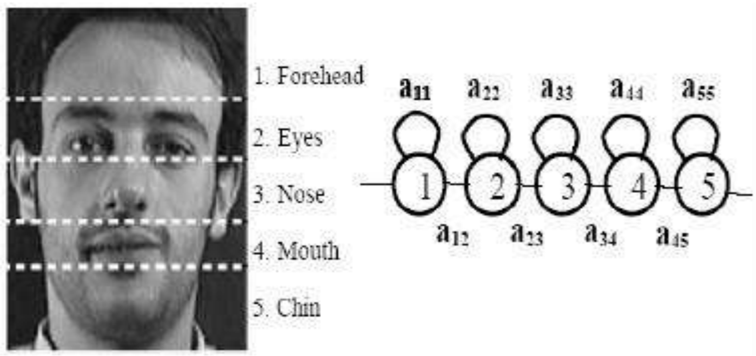


**Fig.II.6:the 5 states of the HMM (from top to bottom).**

For a given person's face image from the training set, the goal of the training step is to optimize the parameters to better describe the observation. Recognition is performed by matching the test image against each training model (each HMM represents a different person). And in the end of this procedure, the image is converted into an observation sequence and the probability is calculated for each recorded pattern.

The pattern with the highest probability indicates the identity of the unknown person [35] [34]. The approach HMM satisfactory recognition performance, however it requires intense calculations which increases execution times.

## II.8 Template matching

Templates can be defined either "manually" or configured using functions. The idea is to calculate the correlation between the candidate image and the template. These methods still encounter some robustness problems linked to variations in light, scale, etc. Sinha [37] [38] uses a set of invariants describing the face model. In order to determine the invariants to changes in luminosity making it possible to characterize the different parts of the face (such as the eyes, cheeks, and forehead), this algorithm thus calculates the luminance ratios between the regions of the face and retains the directions of these ratios.

Yuille et al. [39] used a deformable template to model facial features. This template adapts an elastic model, known a priori, to facial characteristics (eg, eyes). In this approach facial characteristics are described by parametric templates. An energy function is defined to relate the contours, peaks and valleys in the input image to the corresponding parameters in the template. The best fit of the elastic model is found by minimizing an energy function of the parameters. Although their experimental results demonstrate good performance for tracking non-rigid features, a drawback of this approach is that the deformable template must be initialized in the proximity of the object of interest. To detect facial features for face recognition, Brunelli and Peggio [40] used, for each extracted region, an appropriate detector.

**Fig.II.7:Different regions used for the template matching phase.**

For the eyes, nose and mouth regions, they use the direction of the vertical and horizontal gradient. The mouth and nose are located using similar strategies. The vertical position is determined using anthropometric standards. First, a fine estimate of their real position is obtained by looking for the peaks of the horizontal projection of the vertical gradient for the nose, and the valleys of the horizontal projection of the intensity for the mouth.

The position of the eyebrows and their thickness can be found by a similar analysis. The search is once again limited to the window of interest, just above the eyes, and the eyebrows are found using the vertical gradient map. The eyebrow detector looks for pairs of gradient peaks with opposite directions.

## II.9 Active Appearance Models

Active appearance models (AAM) allow texture information to be taken into account, in addition to shape information. They seek to minimize the difference between the original image and a synthetic image, constructed from the average shape, the average texture and a vector of parameters. They rely on PCA to jointly represent the shape and texture variations present in a training set. The "Active Appearance Model" presents a tool for extracting characteristics (signatures) representing both the shape and texture of faces.

## II.10 Graph-based approaches

Rather than using purely geometric methods, some researchers have chosen to represent local facial features in the form of graphs. They are based on Gabor wavelet decomposition. Face recognition is then formulated as a graph matching problem.

However, once constructed, the topological graph cannot be modified. However, face images easily change appearance due to different variations (illumination, expression, pose, etc.), and therefore a fixed topological graph scheme is no longer adequate.

### II.10.1 Elastic Graph Matching

The algorithm EGM “Elastic Graph Matching” is described in DLA Dynamic Link Architecture ,it represents individual faces by a rectangular graph. Each node in the graph is labeled with a set of complex coefficients of Gabor wavelets called jets differing in orientation and scale. A jet is used to represent local features of face images based on the Gabor wavelet transform. Only the magnitudes of the coefficients are used for recognition.

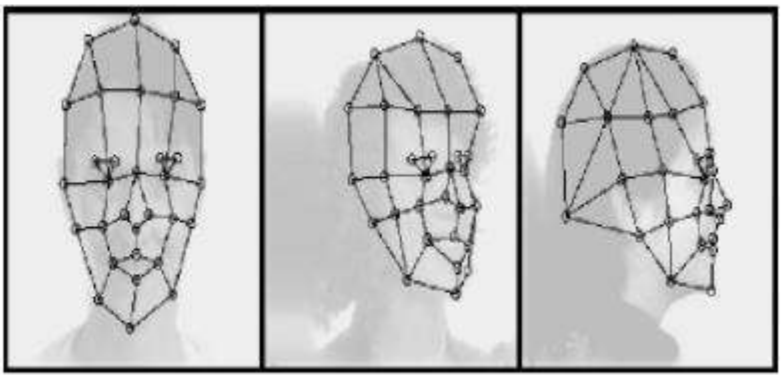

**Fig.II.8:The representation of faces by rectangular graph.**

For the recognition of a new face, each graph in the database is adjusted to this newly constructed graph, and the good adjustment indicates the recognized person.

Encouraging results are obtained when using faces with wide rotating angles. In general the DLA is good in terms of rotation variation, however the recognition or adjustment process is computationally expensive.

L'EGM uses the phase of complex coefficients of Gabor wavelets to achieve more precise localization of nodes and to differentiate similar models in their magnitude coefficients.

L'EGM use of adaptive object graphs “object adaptive graphs”, whose nodes refer to specific facial landmarks, where the trust points “trust points” in the face, namely the pupils, the corners of the mouth and the tip of the nose.

### II.10.2 Elastic Buch Graph Matching

In this approach, characteristic points are located (corners of the eyes, mouth, nose, etc.) from a face image; this localization can be done manually or automatically using an algorithm. A virtual elastic lattice is then applied to the face image from these points.

Each point represents a labeled node to which we associate a set of complex Gabor wavelet coefficients, called Jet. To perform recognition with a test image, we measure the similarity between the different Jets and the lengths of the lattice segments of two images.

The characteristic of EBGM is that it does not directly process the gray level values of the pixels of a face image, which gives it greater robustness to changes in illumination, pose and facial expression. However, it is more difficult to implement than global methods [19].

## II.11 Existing biometric systems for face recognition

Biometric face recognition systems are becoming more and more widespread. Below are some of the systems implemented as well as the different areas of use of this expanding technology: On October 14, 1998, the Borough of Newham of London implemented a system which reduced the number of crimes by 10% in 6 months, thanks to the use of face recognition software called “Mandrake”. The system alerted camera operators as soon as there were 80%matches between the previously digitized image of an offender and what the cameras. Face recognition systems are deployed in air transport, the “Smart Gate” system for example has been implemented in order to carry out automatic identity verification for aircraft crew crossing the border of the Australia. The latter makes a comparison between a person's face and their passport photograph [41].

In January 2002, Visage Technology, the provider of face recognition technology and services, announced the installation of the first face recognition system in Florida at the St. Petersburg-Clearwater International Airport [42].

This technology is also used to identify wanted people by comparing passport photos with a database of wanted people. There are still a whole range of uses for face recognition. Today ATM's (Automatic Teller Machine: Automatic teller machines operated by banks or other financial institutions) identify users not by their bank card numbers, but by also referring to their face. In fact, the ATM captures an image of a face and compares it with the photo from the base in order to confirm its identity. Several companies have oriented their activities towards this technology, we find for example the “Widget” Company which has developed the “Snappy Face” system which makes it possible to identify the face of the owner of the computer to secure its access thanks to a webcam. or even “TitaniumTechnology Enterprise” based in Beijing which developed automatic face recognition software for surveillance (Automatic Face Recognition Systems or AFRS) called “ProFaceriDVR” [43].

## II.12 Conclusion

In this chapter, we presented the main face recognition techniques, then we outlined some systems sold on the market. This enthusiasm for face recognition systems is justified by the numerous advantages of this approach. In fact, this technology is inexpensive, takes up little space, and is also not very restrictive for users.

## I.1 Introduction

Among the different biometrics, the face is the characteristic most used by man to identify a member of his entourage. In order to simulate this biological behavior, researchers began to design increasingly efficient systems. Since then, face recognition has experienced strong development and remains a field that still raises questions and enthusiasm among researchers. Among all the methods presented in the state of the art, some remain more advantageous than others and the criteria used for this selection are based in particular on the execution times and the recognition rates of the latter. This chapter is divided into two parts: in the first part, we describe in detail our technique for feature extraction and data dimension reduction based on Principal Component Analysis (PCA), then we present the LBP approach ( Local Binary Pattern).

## III.2 Eigenface face recognition

### III.2.1 Presentation of the Eigenface method

The ACP algorithm, PCA in English (Principal Component Analysis) and also known as Eigenfaces since it uses eigenvectors and eigenvalues. (respectively Eigenvectors and Eigenvalues). This algorithm relies on well-known statistical properties and uses linear algebra. It is relatively quick to implement but it is sensitive to problems of lighting [20], pose and facial expression. It is the basis of many current global algorithms.

The main idea consists of expressing the M training images according to a basis of particular orthogonal vectors, containing independent information from one vector to another. These new data are therefore expressed in a way more appropriate for face recognition.

We want to extract characteristic information from a face image, to encode it as efficiently as possible in order to compare it against a database of similarly encoded models. In mathematical terms, this amounts to finding the eigenvectors of the covariance matrix formed by the different images of our learning base. An image $I_{i\ (m,n)}$ is treated as a vector $\Gamma_{i\,(m\times n,1)}$ in a space large vector $(N = m \times n)$ , by concatenation of columns.

$$\mathbf{I_1} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} \Rightarrow \mathbf{\Gamma_1} = \begin{pmatrix} a_{1,1} \\ \vdots \\ a_{n,1} \\ \vdots \\ a_{1,m} \\ \vdots \\ a_{n,m} \end{pmatrix}$$

**Fig.III.1:Passage of an image to a column vector.**

The coefficients $a_{i,j}$ represent grayscale pixel values, coded from 0 to 255.

After gathering our M images into a single matrix, we obtain an image matrix Γ, where each column represents an image:

$$\begin{array}{cc} & \hphantom{a_{1,1} \quad b_{1,1} \quad \cdots \quad} \Gamma_i \\ \mathbf{\Gamma} = & \begin{pmatrix} a_{1,1} & b_{1,1} & \cdots & z_{1,1} \\ \vdots & \vdots & \cdots & \vdots \\ a_{n,1} & b_{n,1} & \cdots & z_{n,1} \\ \vdots & \vdots & \cdots & \vdots \\ a_{1,m} & b_{1,m} & \cdots & z_{1,m} \\ \vdots & \vdots & \cdots & \vdots \\ a_{n,m} & b_{n,m} & \cdots & z_{n,m} \end{pmatrix} \end{array}$$

We then calculate the average image Ψ of all the images collected.

This image can be seen as the center of gravity of the set of images (Fig.III.2):

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i \qquad \text{(III.1)}$$

The data is then adjusted relative to the mean.

**Fig.III.2:Average image.**

The average image is then subtracted from each image with the following formula:

$$\Phi_i = \Gamma_i - \Psi, \quad i = 1 \ldots .M \qquad \text{(III.2)}$$

We then calculate the covariance matrix of the dataset. This matrix can be seen as a moment matrix of order 2:

$$C = \sum_{i=1}^{M} \Phi_i \Phi_i^T = AA^T \text{ ,} A = [\, \Phi_1, \Phi_2, \ldots .. \Phi_M] \tag{III.3}$$

The next step consists of calculating the eigenvectors and eigenvalues of this covariance matrix C of size (N × N), that is to say of the order of the resolution of an image. The problem is that it can sometimes be very difficult and very time-consuming. Indeed, if N > M (if the resolution is greater than the number of images), there will only be (M -1) eigenvectors which will contain information [4] (the remaining eigenvectors will have associated eigenvalues null). For example, for 50 images of resolution 180 × 200, we could solve a matrix L of 50 × 50 instead of a matrix of 36000 × 36000 for then take the appropriate linear combinations of the images. The time saving of calculation would be considerable, we would go from a complexity of the order of the number of pixels in an image to that of the order of the number of images.

The steps in the process that allow us to speed up the calculations are described below:

Consider the eigenvectors ei of $C = AA^T$ associated with the eigenvalues $\lambda_i$ We have:

$$Ce_i = \lambda_i e_i \tag{III.4}$$

Eigenvectors vi of $L = A^T A$ , sociated with the eigenvalues are $\mu_i$

$$Lv_i = \mu_i v_i \tag{III.5}$$

Either :

$$A^T A v_i = \mu_i v_i \tag{III.6}$$

Multiplying on the left by A on both sides of the equality, we obtain:

$$AA^T A v_i = A\mu_i v_i \tag{III.7}$$

Since $C = AA^T$, we can simplify:

$$C(Av_i) = \mu_i(Av_i) \tag{III.8}$$

From (III.4) and (III.6), we see $Av_i$ $\mu_i$ that And are respectively the eigenvectors and the eigenvalues of C:

$$\begin{cases} e_i = Av_i \\ \lambda_i = \mu_i \end{cases} \tag{III.9}$$

So we can find the eigenvalues of this huge matrix C by finding the eigenvalues of a much smaller matrix L. To find the eigenvectors of C, simply multiply the eigenvectors of L by the matrix A. The eigenvectors found are then ordered according to their corresponding eigenvalues, in a decreasing manner. The larger an eigenvalue, the more variance captured by the eigenvector is important. This implies that most of the information is contained in the first eigenvectors.

Part of the great efficiency of the PCA algorithm comes from the next step which consists of selecting $k$ only the best eigenvectors (those with $k$ the largest own values). We then define a vector space generated $k$ by these eigenvectors, which we call the space of faces $E_v$ “Face Space".

The original images can be reconstructed by linear combination of these eigenvectors. The graphic representations of these vectors are somewhat reminiscent of ghost images, each highlighting a part of the face, we call them eigenfaces(Fig.III.4).

Practically, the choice of “k” can be made either by setting a certain percentage D such that:

$$\frac{\sum_{i=K+1}^{n} \lambda_i}{\sum_{i=1}^{n} \lambda_i} < D \tag{III.10}$$

With n represents the total number of eigenvalues based on the fact that the $i_{th}$ eigenvalue is equal to the variance along the $i_{th}$ principal component and we search, therefore “k” along the spectrum of eigenvalues just before it vanishes [20].

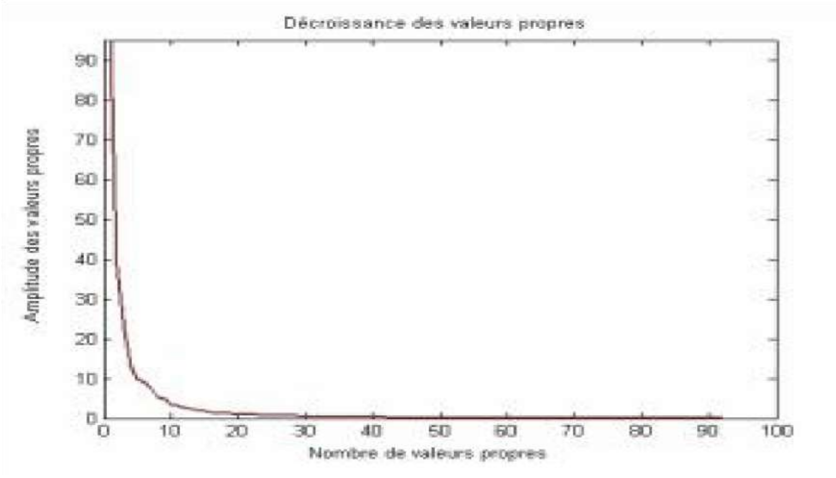


**Fig.III.3:Decrease of the eigenvalues of the database used depending on the number of eigenvectors retained.**

Therefore, the first “k” eigenvectors corresponding to the “k” largest eigenvalues are a critical parameter on which the performance of the face recognition system depends (computation time and recognition rate) and also an evaluation criterion [ 20] methods based on PCA.

From there, we define a vector space generated by these k eigenvectors, which we call the face space (Face Space). The original images can be reconstituted by linear combination of these eigenvectors. The graphic representations of these vectors are somewhat reminiscent of ghost images, each highlighting a part of the face, we call them Eigenfaces (Fig.III.4).

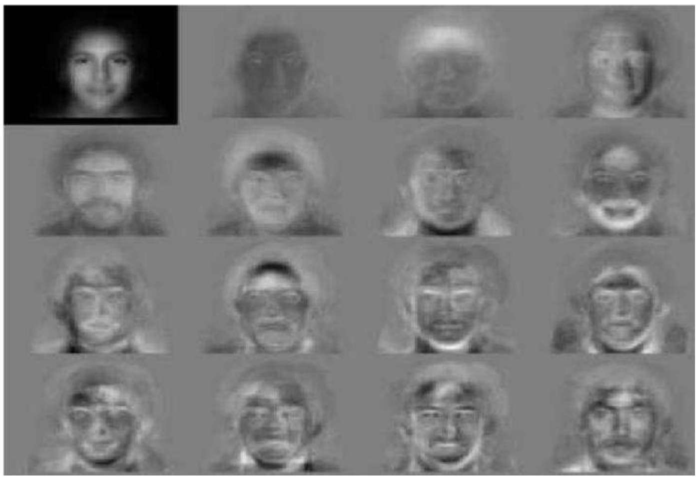

**Fig.III.4:eigenfaces.**

### III.2.2 Use of Eigenfaces for the classification of face images

We will now project our initial images onto . A $E_v$ picture $\Gamma_i$ is then transformed into its Eigenfaces components by a simple vector projection operation vectors.

$$\omega_K = e_K^T(\Gamma_i - \Psi), K = 1, \dots, M' \quad \text{(III.11)}$$

Vectors $\omega_K$ are called weight vectors and form a matrix [44] $\Omega_T$ = [$\omega_1$, $\omega_2$ . , , $\omega_{M0}$ ] which describes the contribution of each eigenface in the representation of the input image. The matrix $\Omega_T$ is then used to find which is, among a number predefined classes, the one that best describes an input image.

The simplest method to determine which face class provides the best description of an input image is to find the face class $k$ which minimizes the distance Euclidean.

$$\varepsilon_K^2 = \|\Omega - \Omega_K\|^2 \quad \text{(III.12)}$$

Or $\Omega_K$ is a vector that describes the $k_{th}$ face class.

A face belongs to a class k when the minimum $\varepsilon_K$ is below a certain threshold $\theta_\varepsilon$ Otherwise, the face is classified as unknown and may possibly be used to create a new face class. The creation of the matrix weight $\Omega^T$ is equivalent to the projection of the original face on $E_v$. Since the distance between the face image and is simply the square of the distance between

$$\Phi = \Gamma - \Psi \qquad \Phi_f = \sum_{i=1}^{M'} \omega_i e_i$$

the input image readjusted relative to the mean And , its projection on is: $\varepsilon^2 = \|\Omega - \Omega_K\|^2$.

There are then four possibilities (Fig.III.5) for an input image to be recognized or not:

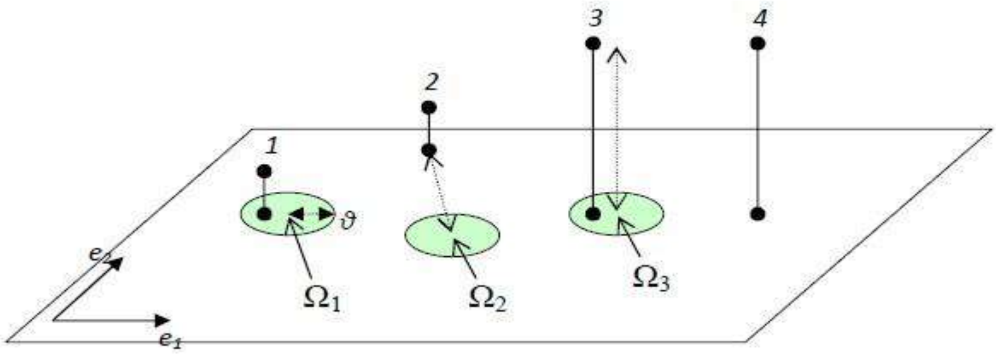


**Fig.III.5:Illustration of possible cases of classification of an image.**

- ✓ Case 1: an individual is recognized and identified.
- ✓ Case 2: an individual unknown to the system is present.
- ✓ Cases 3 and 4: indicate that the image is not a face image.

.

### III.2.3 Main stages of the Eigen faces technique

The learning of clean faces is carried out according to the following steps:

1) Collection of M facial images and construction of the matrix T of size M, by concatenation of the columns of the facial images. Preprocessing of collected images.
2) Calculation of the average face by summing the columns of the matrix T and dividing the resulting vector by the number of input images (M).
3) Subtraction of the average face from the matrix T to obtain the matrix A; where each element represents the variance of the intensity values of each pixel.
4) Calculation of the matrix ,$C'$ $C' = A^T A$ .
5) Calculation of the eigenvectors of C' and sorted them in descending order according to the associated eigenvalues.
6) Calculation of the eigenvectors of the covariance matrix C and obtaining the eigenfaces by multiplying the eigenvectors of C' by the matrix A.
7) Choice of the K best eigenvalues and the associated eigenvectors.
8) Determining the weight of the input images by projecting each image into face space.

9) Each face is now represented by a vector which is used to reconstruct the images. then we save the average face, the eigenfaces and the projection (weight) matrices of the images.

The nine steps described will transform a database of facial images into a set of face space projections.

The recognition stage can be summarized as follows:

- Preprocessing the input image and subtracting the average face.
- Determination of the weight of the input image by projecting it into the face space by multiplying the vector resulting from step (1) by the faces of the database.
- Comparison of results obtained using metrics such as Euclidean distance.

## III.2.4 Distance Measurements

When we wish to compare two feature vectors from the feature extraction module of a biometric system, we can either perform a similarity measurement (resemblance) or a distance measurement (divergence).

The first category of distances consists of Euclidean distances and are defined from the Minkowski distance of order p in a Euclidean space (determining the dimension of the Euclidean space).

Consider two vectors $X = (x_1, x_2, \dots \dots, x_n)$ $Y = (y_1, y_2, \dots \dots, y_n)$ distance of Minkowski order p :

$$L_p = (\sum_{i=1}^{n} (|x_i - y_i|)^p)^{1/p} \quad \text{(III.13)}$$

We will present some distance measurements in the original image space and then in the Mahalanobis space.

### III.2.4.1 Euclidean Distances

#### A. Distance City Block (L1)

For p = 1, we obtain the City-Block distance (or Manhattan distance):

$$L_1(x, y) = \sum_{i=1}^{n} |x_i - y_i| \quad \text{(III.14)}$$

**B. Euclidean Distance (L2)**

For p = 2, we obtain the Euclidean distance:

$$L_2(x,y) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \quad \text{(III.15)}$$

Objects can then appear in very different ways depending on the distance measurement chosen (Fig.III.6).

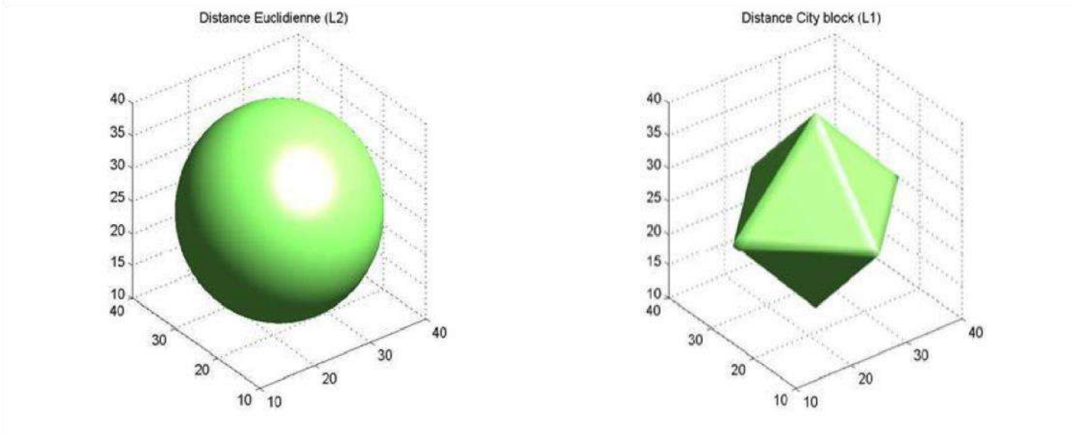


**Fig.III.6:Representation of a sphere with Euclidean distance (3.4.a) and the City-Block distance (3.4.b).**

### III.2.4.2 Distances in Mahalanobis Space

**A- From the space of images to the space of Mahalanobis**

Before we can perform distance measurements in Mahalanobis space, it is essential to understand how we go from Im image space to Mahalanobis $\varepsilon_{Mah}$ space.

At the output of the PCA algorithm, we obtain eigenvectors associated with eigenvalues (representing the variance along each dimension). These eigenvectors define a rotation towards a space whose covariance between the different dimensions is zero. The Mahalanobis space is a space where the variance along each dimension is equal to 1. It is obtained from the space of images Im by dividing each eigenvector by its corresponding standard deviation.

Let u and v be two eigenvectors of $I_m$, from the PCA algorithm, and m And n two vectors $\varepsilon_{Mah}$ . Let $\lambda_i$ the eigenvalues associated with the vectors m relationships following:

$$m_i = \frac{u_i}{\sigma_i} = \frac{u_i}{\sqrt{\lambda_i}} \text{ And } = \frac{v_i}{\sigma_i} = \frac{v_i}{\sqrt{\lambda_i}} \qquad \text{(III.16)}$$

**B- Mahalanobis L1 (MahL1)**

This distance is exactly the same as the City-Block distance except that the vectors are projected into Mahalanobis space. Thus, for eigenvectorsuAndv of respective projections m And n to Mahalanobis space, the Mahalanobis distance is defined by:

$$Mah_{L1}(u,v) = \sum_{i=1}^{N} |m_i - n_i| \qquad \text{(III.17)}$$

**C- Mahalanobis L2 (MahL2)**

This distance is identical to the Euclidean distance except that it is calculated in Mahalanobis space. Thus, for eigenvectors u and v with respective projections m and n on the Mahalanobis space, the Mahalanobis distance is dened by:

$$Mah_{L2}(u,v) = \sqrt{\sum_{i=1}^{N} |m_i - n_i|^2} \qquad \text{(III.18)}$$

By default, when we talk about Mahalanobis distance, it is to this distance that we must refer.

### III.2.4.3 Mahalanobis cosine (MahCosine)

It is simply the cosine of the angle between the vectors u And v, once they have been projected onto and normalized by variance estimators (Fig.III.7).

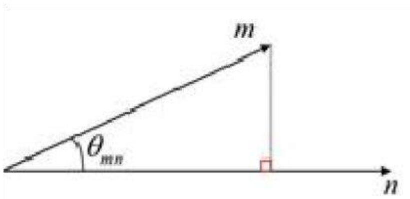


**Fig.III.7:The two vectors m and n in Mahalanobis space.**

We therefore have by definition:

$$S_{Mahcosine}(u,v) = \cos(\theta_{mn}) \qquad \text{(III.19)}$$

Additionally, we can write:

$$\cos(\theta_{mn}) = \frac{|m||n|\cos(\theta_{mn})}{|m||n|} \qquad \text{(III.20)}$$

Hence the final formula for the similarity measure MahCosine:

$$S_{Mahcosine}(u,v) = \frac{mn}{|m||n|}, D_{Mahcosine}(u,v) = -S_{Mahcosins}(u,v) \qquad \text{(III.21)}$$

### III.2.4.4 Choice of similarity distance

In the pattern recognition community, the choice of a similarity distance is often explained and argued with respect to the attribute space and data points used. We noticed among other things, with the same Eigen faces attribute vectors, that the Euclidean distance provides better results for identifying individuals than with the Manhattan distance. These performances pushed us to use the Euclidean distance in this last process.

### III.2.5 Detailed flowchart of the Eigenface approach

Our flowchart is divided into three parts: the first is the preprocessing followed by the learning phase and ends with the identification phase where the Euclidean distance is used to calculate the difference between the weights of the image to be identified and database images then the program displays the closest one.

### III.2.5.1 Preprocessing flowchart

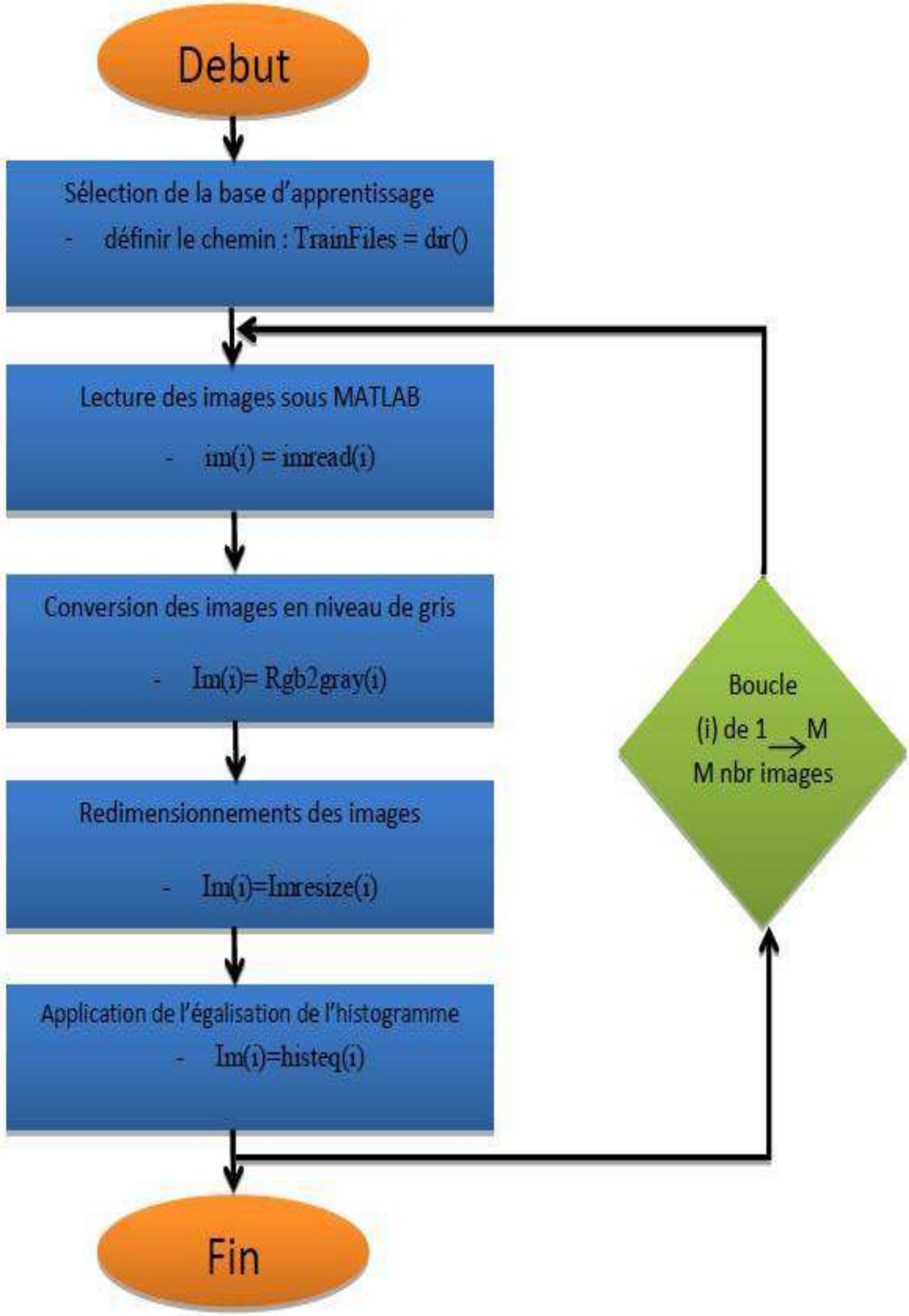


**Fig.III.8:pretreatments.**

### III.2.5.2 Flowchart of the learning phase

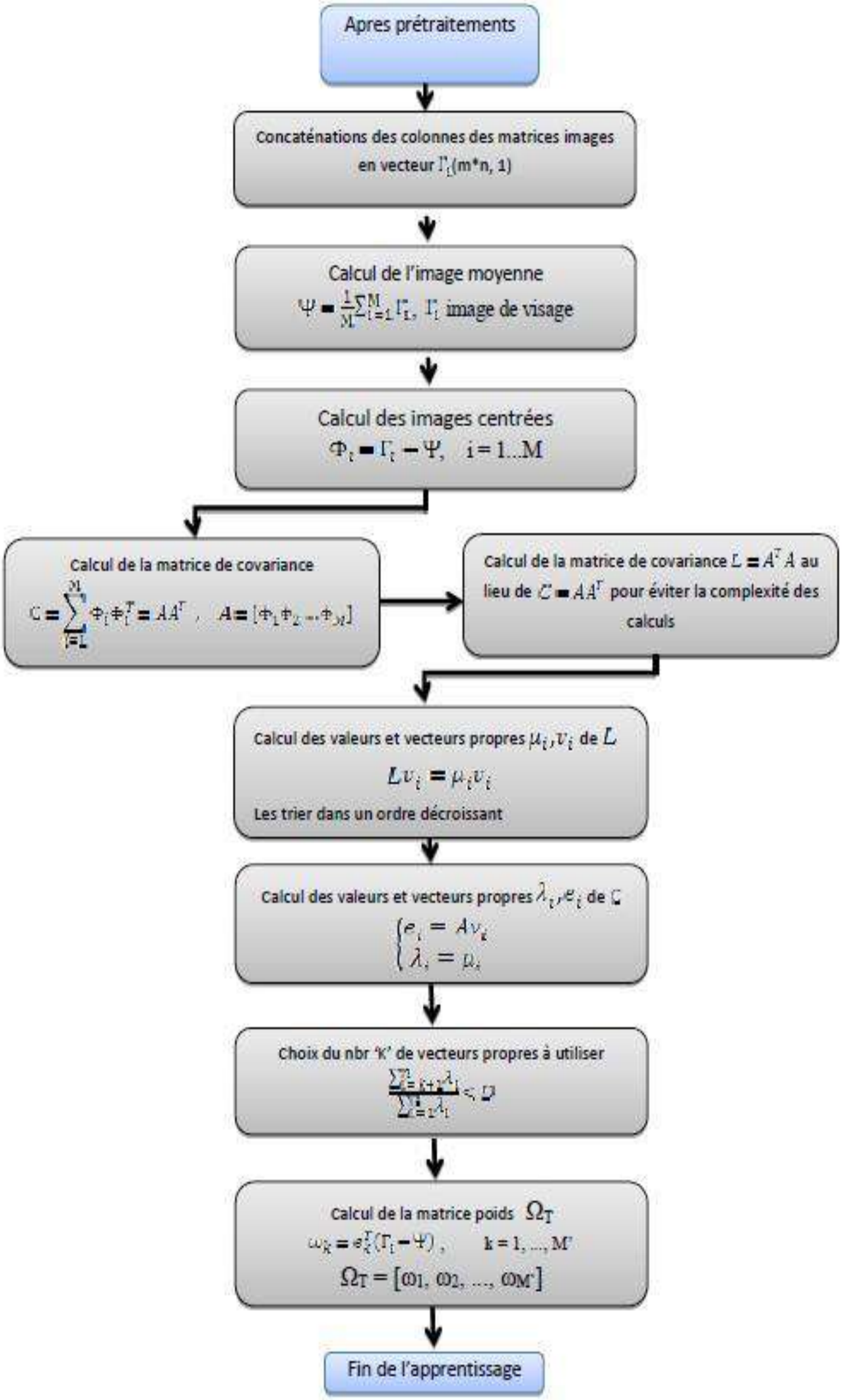


**Fig.III.9:learning phase.**

### III.2.5.3 Organization chart of the identification phase

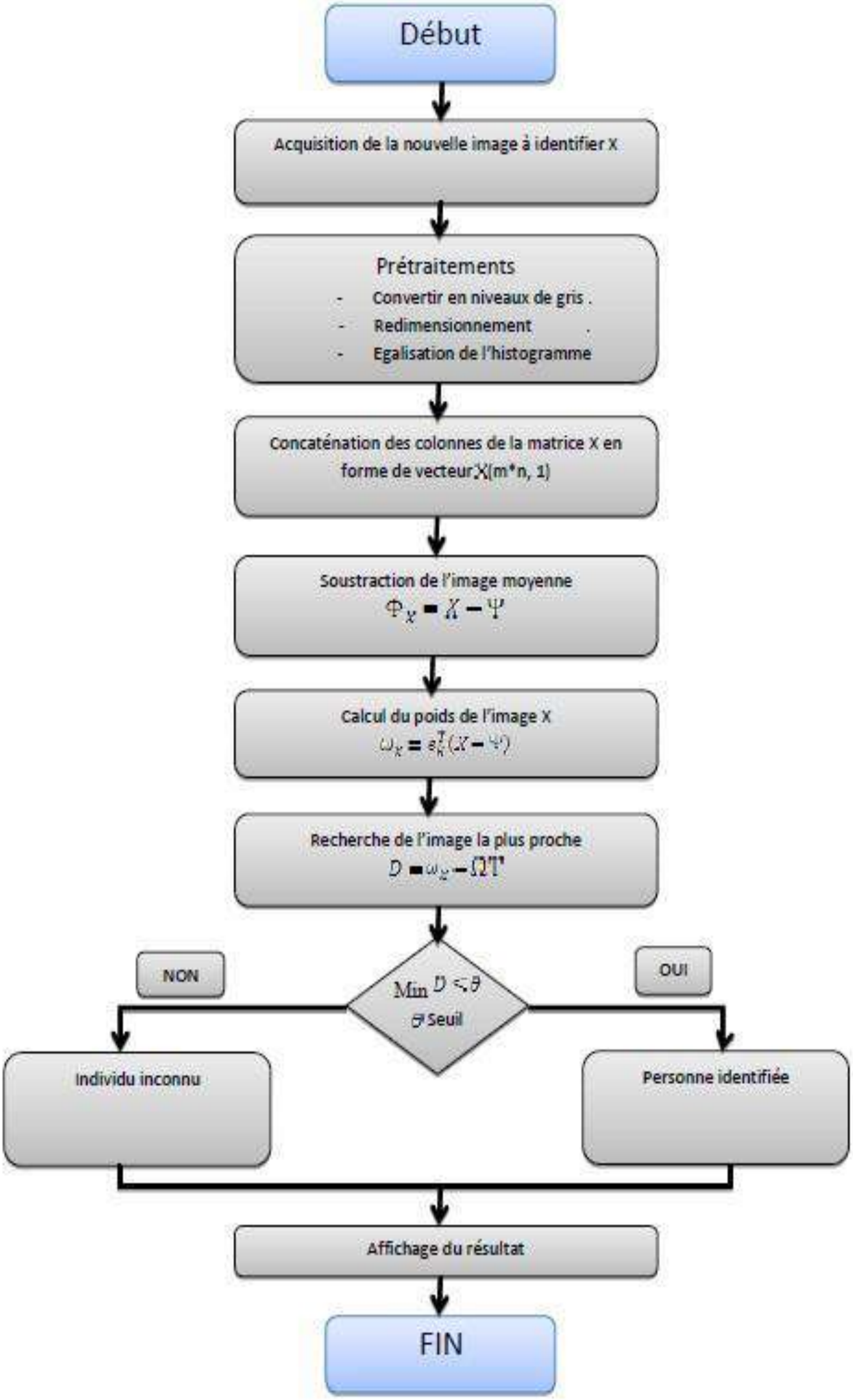


**Fig.III.10:identification phase.**

## III.3 Face recognition by Local Binary Pattern (LBP)

### III.3.1 Presentation

The operator (LBP) was initially proposed by Ojala et al. [45] with the aim of characterize the texture of an image. Calculating the value (LBP) consists for each pixel of threshold its eight direct neighbors with a threshold whose value is the gray level of the current pixel. All neighbors will then take a value 1 if their value is greater than or equal to the current pixel and 0 if their value is lower (Fig.III.11). The current pixel code (LBP) is then produced by concatenating these 8 values to form a binary code.

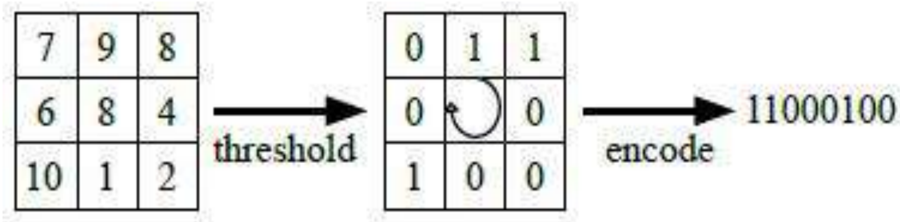


**Fig.III.11:LBP operator.**

The technique (LBP) was later extended using neighborhoods of size deferential. In this case, a circle of radius R around the central pixel and the values of the P points sampled on the edge of this circle are taken and compared with the value of the central pixel. To obtain the values of the P sampled points in the neighborhood for any radius R, interpolation is necessary. We adopt the notation (P, R) to define the neighborhood of P points of radius R of a pixel. Fig.III.12 (a),

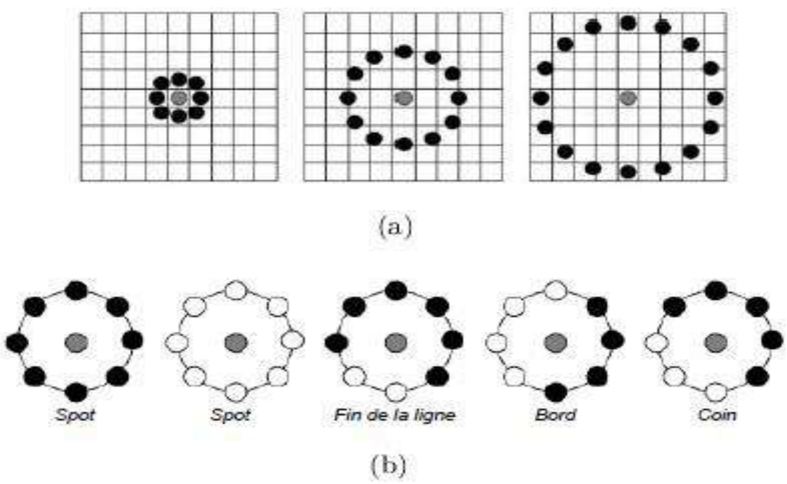


**Fig.III.12:(a): Three neighborhoods for different R and P, (b): Particular textures detected by (LBP)**

Let $g_c$ the gray level of central $g_p$ $(P = 1 \dots P)$ pixel,the gray levels of its neighbors.

The LBP

$$\mathrm{LBP}_{P,R}\ (x_c, y_c) = \sum_{P=1}^{P} S(g_p, g_c) 2^{P-1} \quad \text{(III.22)}$$

Or

$$S(x) = \begin{cases} 1 \ if\ x \geq 0 \\ 0 \ if\ x < 0 \end{cases} \quad \text{(III.23)}$$

### III.3.2 LBP for face recognition

Once the code LBP has been calculated for all the pixels of the image, we calculate the histogram of this image to form a feature vector representing the facial image. In reality, in order to incorporate more spatial information into the vector representing the face, we first divide the image coded by the operator LBP into small regions and the histogram is built for each region. Finally, we concatenate all the histograms of the regions in order to form a large histogram representing the image of the facial characteristics (see Fig.III.13). Code efficiency LBP as a facial index is explained by the fact that the LBP allows you to characterize the detailsof a face. When only the LBPs uniforms are used, all codes LBPs non-uniforms are labeled with a unique label, then that each of the uniform codes is grouped into a single histogram. For example, when P = 8, we have 58 uniform codes but the histogram is of dimension 59. Similarly P = 6 produces a histogram of dimension 33.

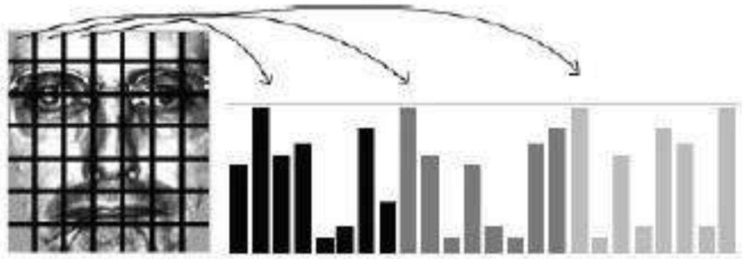

**Fig.III.13:Representation of a face by histograms of the LBP code.**

Given two histograms of $LBP\ H^1,H^2$ of two faces, the next step is to use a metric to calculate the similarity between these two histograms. By testing the three metrics, $X^2$ Histogram intersection and Log-likelihood statistic ,Ahonen et al. [47] have observed that the first metric achieves the best results:

$$X2(H^1,H^2) = \sum_i \frac{(H_i^1 - H_i^2)^2}{H_i^1 + H_i^2} \qquad \text{(III.24)}$$

### III.3.3 Latest advances: Work by Tan and Triggs

Their work [48] follows that of Ahonen et al. It offers 3 new concepts which significantly improve performance (more than 40% on the FRGC-104 database according to their publication). These three concepts are Local Ternary Patterns (LTP), an image preprocessing method and finally a distance measurement method for comparing samples in LBP or LTP format. These concepts are detailed below.

#### III.3.3.1 Local ternary patterns

This is the generalization of local binary patterns to the ternary system. It was proposed by Tan and Triggs [48] as a solution to the sensitivity problem experienced by LBP in the face of random noise and that of quantification. The principle is as follows:

while the LBP applied a threshold equal to the value of the central pixel, the conversion to Local Ternay Patterns (LTP) assigns the value 0 to pixels whose value is in a neighborhood of the value of the central pixel, 1 to those whose the value is beyond this neighborhood and - 1 to those whose value is below. The mathematical formulation is as follows for u a peripheral pixel of a surrounding to be converted, IC the value of the central pixel and t the neighborhood:

$$S(u, i_c, t) = \begin{cases} 1 \; si \; u \geq i_c + t \\ 0 \; si \; |u - i_c| < t \\ -1 \; si \; u \leq \; i_c - t \end{cases} \tag{III.25}$$

As done for the basic LBP operator, an illustration of the basic LTP operator is made in Fig.III.14.

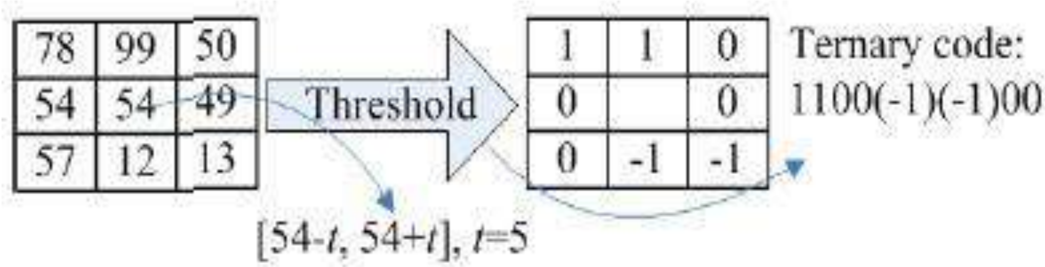


**Fig.III.14:Basic LTP operator.**

Then, this ternary code can be transformed into either a real number or a binary code to move on to the next phase. In the first case we could use a value code similar to the binary code. Tan and Triggs split the ternary code into two binary codes processed separately and then brought together during the comparison phase. This method has the advantage of keeping the system simple for eliminating non-uniform patterns.

### III.3.3.2 The image preparation method

This is carried out in three stages:

1. Gamma correction. The basic idea is that as the image reflected by a face is the product of the light reaching it by the reflectance of the surface, a variation in reflectance representing a discriminative feature will have a relative influence on the illumination that she undergoes, thereby introducing a bias. The proposed solution is to apply the logarithmic operator by which this product will become a sum. Thus, for uniform local illumination, a jump in reflectance x will cause the same increment on the reflected image whatever the starting illumination value. However, according to Tan et al., a logarithm tends to amplify the noise too much in dark areas. For this reason, an exponent

in the range [0, 0.5] is used instead of the logarithm. Thus the first step is described by the mathematical relation:

$$I'(i,j) = I(i,j)^{\gamma}$$

Or $I(i,j)$ is the intensity of the coordinate pixel $(i,j)$ of the input image $I'$ and the image resulting from this first preprocessing step.

2. Filtering by difference of Gaussians. This is the implementation of a band pass to remove low frequencies containing unwanted shadow effects and high frequencies containing aliasing and noise.
3. Contrast equalization. This is carried out in three steps on the region delimiting the face.

$$I(x,y) \leftarrow \frac{I(x,y)}{(mean(|x',y'|^{a}))^{1/a}}$$

$$I(x,y) \leftarrow \frac{I(x,y)}{(mean(\min(T,|I(x',y')|)^{a}))^{1/a}}$$

$$I(x,y) \leftarrow Ttank(\frac{I(x,y)}{T}$$

The application of this method to the same face subjected to different illumination conditions is illustrated in FIG.III.15.

**Fig.III.15:Illustration of the application of the proposed illumination correction method by Tan and Triggs.**

### III.3.3.3 The metric used to compare two histograms

The distance measurement proposed by Tan and Triggs intrinsically takes into account the spatial organization of the LTPs distributed over the entire image. No more question of histogram here either. Consider two images to compare and . For each LTP (also (number of pixels) of , the method will look among the LTPs of the same value of the closest one and use the distance between them to increment proportionally to the overall distance.

Finally, the distance between two images X and Y is calculated as follows:

$$D(X,Y) = \sum_{pixels(i,j)\ of\ Y} \omega\left(d_x^{kY(i,j)}(i,j)\right) \qquad \text{(III.26)}$$

.

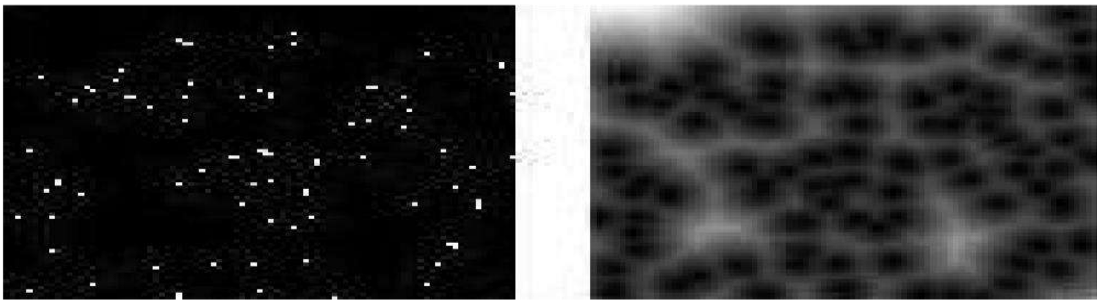

**Fig.III.16:Left: Example of binary pattern distribution matrix. To the right Corresponding distance matrix.**

## III.4 Conclusion

This chapter was devoted to the presentation of the two facial recognition methods used in this work, in this case principal component analysis known as “Eigenface” and the second technique is based on the use of the descriptor LBP, These techniques make it possible to reduce the number of components while keeping the information characterizing the object to be analyzed without loss of significant information.

In the following chapter, we will test the system in its environment in order to evaluate its performance to deduce the optimal parameters which guarantee better system efficiency.

## IV.1 Introduction

To evaluate the effectiveness of the methods described in chapter III, we opted for validation on standard "ORL" and "FEI" databases. Our work consists of designing a biometric identification system for people by facial recognition based on a principal component analysis and calculation of the value which can LBP be used to simplify a set of data, by reducing its dimension. Several steps are necessary, the feature extraction step is the most important because the performance of the system depends on it (results and robustness, an acceptable latency time for "real-time" applications). In this chapter we will evaluate the results obtained on the ORL and FEI databases under different conditions and attributes of the methods.

## IV.2 Face databases

Several databases containing information that allows the evaluation of Face Recognition Systems are available. However, these databases are generally adapted to the needs of a few specific recognition algorithms, each of them has been built with various conditions for acquiring images of faces (changes in illumination, pose, facial expressions ) as well as the number of sessions for each individual.

### IV.2.1 ORL

The data used to carry out the tests on our system come from the ORL database [49]. This database was collected between April 1992 and April 1994 by the AT&T laboratory at the University of Cambridge. The database contains 40 people, each recorded under 10 different views (figure IV.1). The images are 112 × 92 pixels in JPG and BMP format (gray format laptop). For some subjects, images were collected on different dates, with variations in lighting conditions, facial expressions (neutral expression, smile and closed eyes) and partial occlusions by glasses. All images were collected on a dark background. Head poses have some variations in depth compared to the frontal pose.

**Fig.IV.1:Examples of facial images from the ORL database.**

### IV.2.2 FEI

The FEI Face Database is a Brazilian face database that contains a set of face images taken between June 2005 and March 2006 at the FEI Artificial Intelligence Laboratory in São Bernardo Do Campo, São Paulo, Brazil . It contains face images of 200 people, with 14 images for each of them, a total of 2800 images. All images are in color and taken against a consistent white background in a frontal position with various pose angles of each person, extending from profile to frontal views. The lighting variation is 10% and the image resolution is 640x480 Pixel [50].

**Fig.IV.2:Examples of facial images from the FEI database.**

### IV.2.3 Separation of databases

In order to develop a face recognition application, it is necessary to have two databases: one base to carry out the learning and another to test the techniques and determine their performance, but there is no rule for determine this sharing quantitatively. It often results from a compromise taking into account the number of data available and the time to carry out the learning. In the test series that we carried out, the database was split as follows:

•**Learning images :**The first 6 images are used for the learning phase.
•**Test Images :**The last 4 images of each individual were used to carry out the various tests.

The goal is to evaluate the recognition rate of different algorithms presented, by following a test protocol based on the measurement of recognition rate.

**Recognition rate = number of test images recognized / total number of test images**

### IV.3 Work environment

In this section, we will introduce the hardware and software environments of our work.

#### IV.3.1 Hardware environment

In order to carry out this project, a set of materials was made available to us with the following characteristics:

A COMPAQ computer with the following characteristics:

- Processor: Intel® Pentium® Dual CPU T3400 @ 2.16Ghz 2.17Ghz
- RAM: 2.00 GB of RAM
- Hard Drive: 250 GB
- OS: Microsoft Windows 10

#### IV.3.2 Development tools

When developing our system, we used Matlab 10.12.0 which we will present below.

##### IV.3.2.1 Matlab 10.8.0 (R2024a)

Matlab and its interactive environment is a high-level language that allows the execution of tasks requiring large amounts of computing power and whose implementation will be much simpler and faster than with traditional programming languages such as C, C++. It has several toolboxes, in particular the Image Processing ToolBox, which offers a set of reference algorithms and graphic tools for processing, analysis, visualization and development of algorithms. image processing.

## IV.4 Facial recognition system: principles and experiments

The problem of face recognition is defined as follows: given a face image for which we wish to determine the identity of the corresponding person. To do this, it is necessary to have reference images, in the form of a database of faces of all the people known to the system. Each image is associated with a vector of characteristics, these characteristics are supposed to be invariant for the same person, and different from one person to another. Recognition then consists of comparing the vector of facial characteristics to be recognized with that of each of the faces in the database. This makes it possible to find the person with the most similar face, which is the one whose vector is the most similar.

### IV.4.1 PCA-based facial recognition system: Experimentation and results

From the recognition system presented in Fig.III.10 of Chapter III, different tests were carried out depending on different numbers of eigenvectors. The database used is the Olivetti Research Laboratory also called ATT face database [49] and has been split into two sub-bases, one for training and the other for testing.

A preprocessing step is first carried out in order to make the images to be compared homogeneous. This preprocessing is performed on both the training database images and the question image. This converts all images to an identical format to ensure data consistency.

After gathering the faces in a single matrix, we obtain a matrix grouping all the faces. We then calculate the average face of all its collected images. This image can be seen as the center of gravity of all matrices. The data is then adjusted relative to the mean. The average image is then subtracted from each image in the database
(Fig. IV.3).

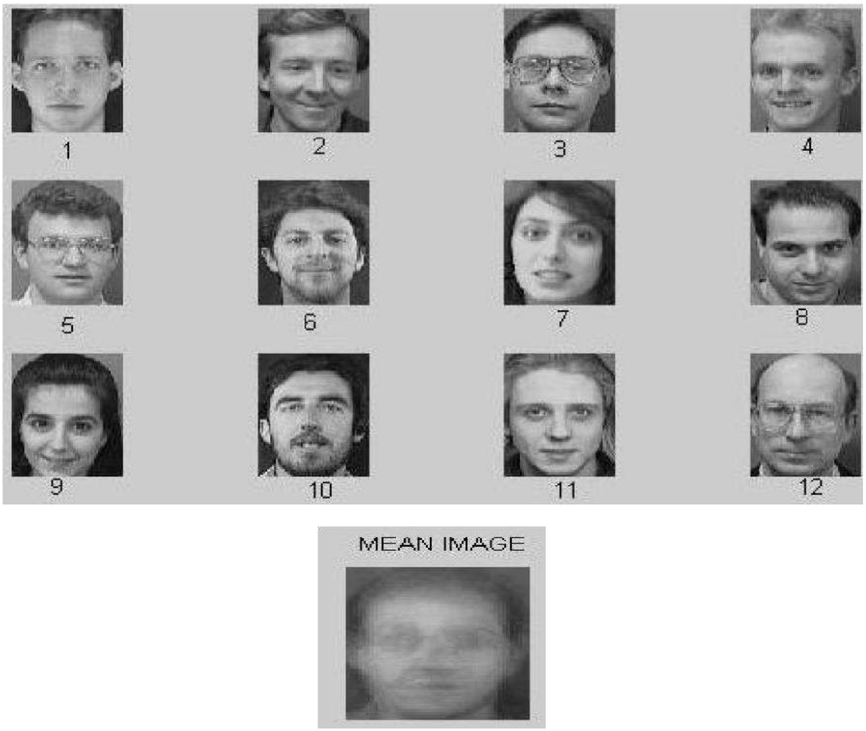


**Fig.IV.3:faces of the ORL database normalize and their average face.**

The figure below (Fig.IV.4) illustrates the growth of the eigenvalues of the covariance matrix of the ORL face database images. We notice on the curve that with just half of the eigenvalues of the covariance matrix we can represent more than 90% of the information which can allow us to take part of the eigenvectors corresponding to the largest eigenvalues.

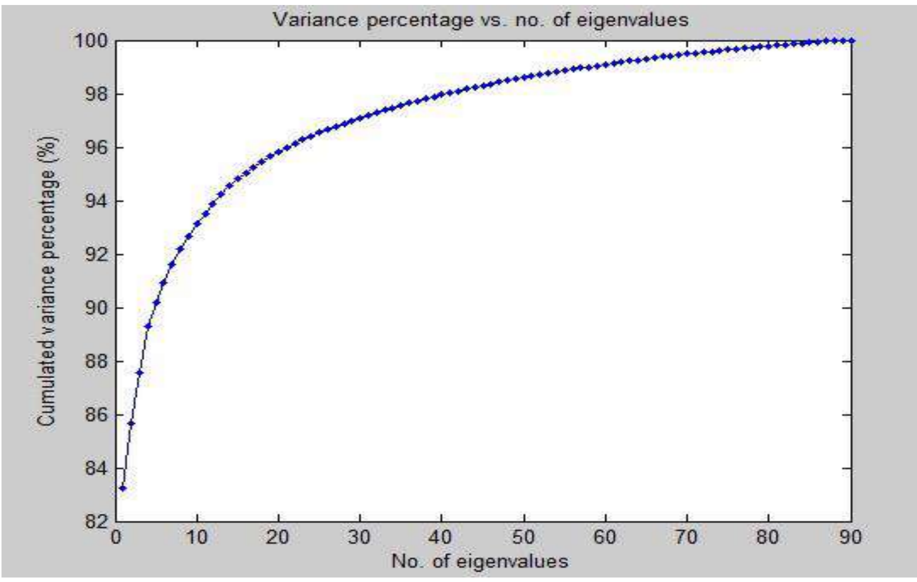


**Fig.IV.4:Eigenvalue plot.**

The possible number of eigenfaces (Fig.IV.5) is equal to the number of face images in the entire learning base. However, faces can be approximated, using only the best Eigenfaces (having the largest eigenvalues which in fact account for the most variance in the set of face images), thus reducing calculations.

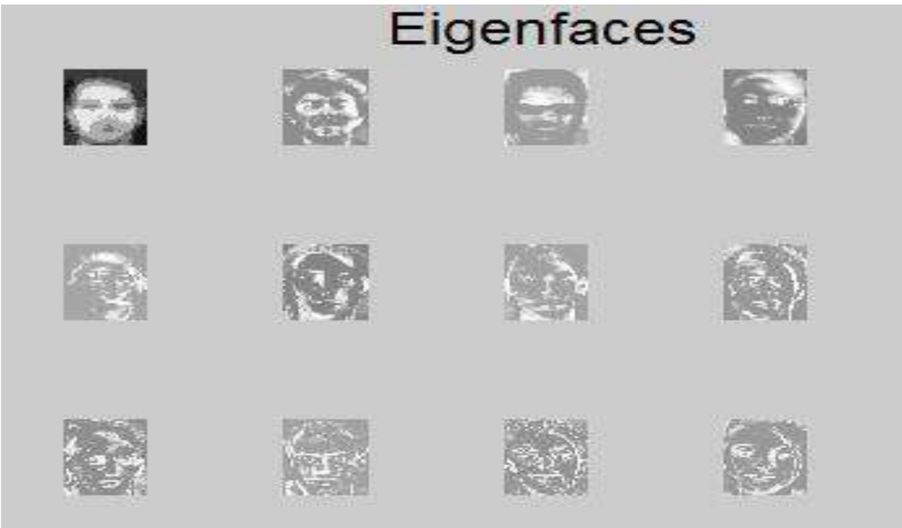


**Fig.IV.5:Eigen faces.**

After calculating the eigenvectors (eigenfaces), the classification step is the phase in which the face recognition system assigns a test face to a class among those in the learning base according to a certain well-chosen criterion. In our case we used the Euclidean distance.

- The first experiment consists of taking several galleries from the ORL database, each of these galleries presents variations due to changes in illumination, pose, facial expression or the presence of structural components such as the wearing of glasses, then we calculate the recognition rate (%) of each as illustrated in Tab.IV .1.

**Fig. IV.6:Example of changing illumination (gallery 1).**

**Fig.IV.7:Example of changing facial expressions (gallery 2).**

**Fig.IV.8:Example of pose change (gallery 3).**

**Fig.IV.9:Example of neutral individuals with different ages (gallery 4).**

| Galleries | Number of images training | Number of images test | Rate acknowledgement |
|---|---|---|---|
| Gallery 1 | 60 | 40 | 75% |
| Gallery 2 | 60 | 40 | 82.25% |
| Gallery 3 | 80 | 60 | 88.33% |
| Gallery 4 | 100 | 70 | 91.42% |

**Tab.IV.1:Recognition rate (%) obtained for different galleries in the ORL database.**

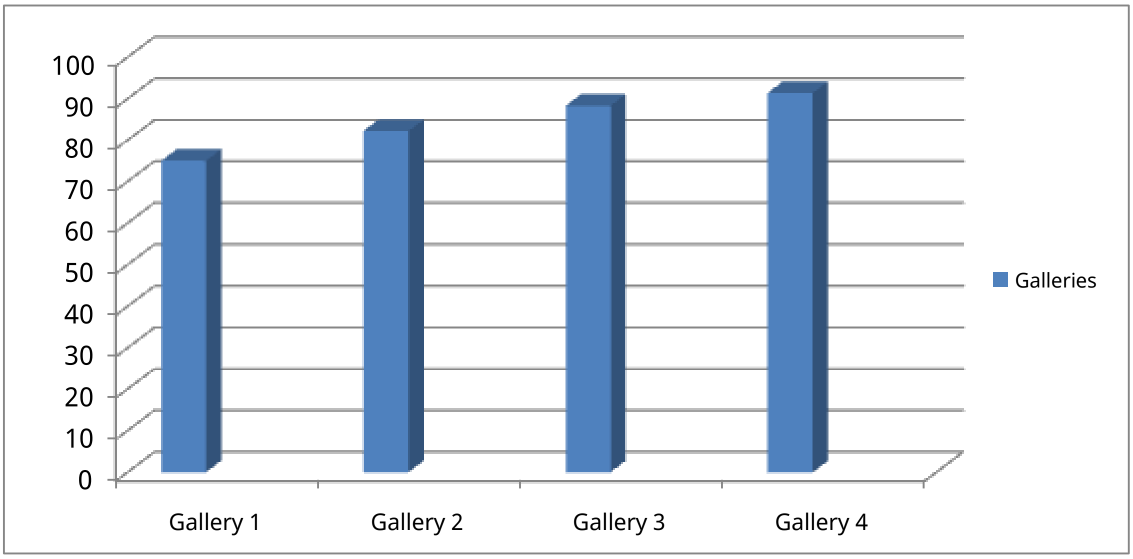


**Fig.IV.10:Recognition rates obtained for different galleries.**

❖ The following experiment consists of taking different numbers of eigenvectors (Eigenfaces) which makes it possible to reduce the calculation time and then evaluate the recognition rate (%). Tab.IV.2 compares the results obtained using different percentages of eigenfaces.

| Percentage of Eigenfaces | 40% | 50% | 60% | 75% | 100% |
|---|---|---|---|---|---|
| Rate acknowledgement | 28.5% | 41.43% | 48.56% | 68.57% | 91.42% |

**Tab.IV.2:Recognition rate (%) obtained according to different numbers of vectors clean.**

❖ The third experiment illustrates the influence of the number of training examples on recognition performance. in the experiment, we fixed the number of test faces. On the other hand, the number of learning faces varies. Thus, for each person, we used the last two images for the test and we randomly chose the first n images (n<= 8) for training.


**Fig.IV.11:Identification rate depending on the number of learning examples per person (ACP).**

From Fig.IV.11 we notice that the performance of the eigenfaces method decreases with the reduction in the number of training examples for each person. In the extreme case, if only one or two training examples per person are used, the average PCA identification rate drops below 60%. On the other hand, this rate reaches 93% when we use eight learning examples per person.

### IV.4.2 Facial recognition system based on LBP: Experimentation and results

The LBP (Local Binary Patterns) facial recognition method consists of visualizing the value of a pixel (average of the three RGB components) in relation to neighboring pixels. To begin, the image is divided into groups of pixels. Each group of pixels corresponds to a square matrix containing the pixel values. Then, the pixel placed in the center of the matrix is chosen as the reference value. Then all values in the matrix are replaced with either 0 or 1 depending on their value. We assign the value 0 if the pixel value is less than the reference pixel value, 1 otherwise. After this operation, each pixel in the group is weighted with a greater or lesser weight (the pixel at the top left has the lowest weight, while the pixel at the bottom right has the highest weight). Thus, we obtain a binary number which gives a certain value in base 10. All the groups of the image are subjected to this process to finally obtain a histogram of the image. Finally, all that remains is to differentiate between two histograms to compare two images.

The basic LBP operator takes a 9-pixel square as input and has an 8-bit binary number as output. The motivation that pushed us to use this operator is that a face can be seen as an assembly of micro-patterns whose description by LBP is both good, robust against gray variations and quick to generate. This simple operator has been extended to remain reliable at different scales.

Thus, P points describe the binary number and these are distributed along a circle of radius R. This surrounding will be noted (P;R). As these P points do not necessarily fall at the center of a pixel of the image, their values are obtained by bilinear interpolation. This is illustrated in Fig.IV.12.

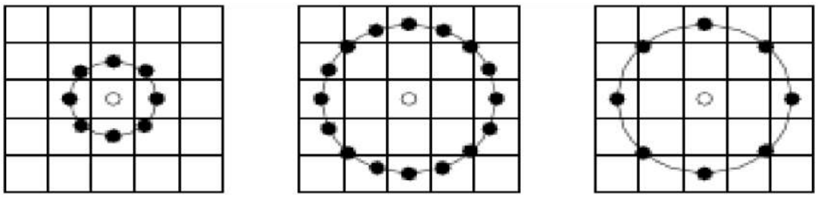

**Fig.IV.12:the basic LBP operator. The surrounds (8,1), (16,2), (8,2) are Represented.**

Then only 'uniform' patterns presenting at most two 1-0 or 0-1 transitions are kept when viewed as circles. Thus 00110000 and 10000001 are uniform while 10010001 and 11011101 are not.

In practice, the conversion of a non-uniform pattern gives the result 0. We thus realize that 90% of patterns (8; 1) belong to the uniform category. This extension allows LBP to be interpreted in terms of inclined corners and edges.

Then to include information regarding the spatial arrangement of the textures and avoid being limited to a holistic description of the textures which would suffer from the known limitations of methods of this type, the converted image is divided into several sub-regions for which as many LBP histograms will be made. Thus for 4 subregions, 4 histograms will be generated. These will be concatenated to form a 2dimensional matrix called a spatially enhanced histogram. Note that the subregions can overlap and do not necessarily have to be rectangular.

The comparison of two spatially improved histograms involves on the one hand establishing a method for measuring the distance between two simple histograms and on the other hand the use of weights to bring together the distances obtained for each sub-region.

| (P;R) | (8.1) | (8.2) | (16.1) | (16.2) |
|---|---|---|---|---|
| **Rate acknowledgement** | **75%** | **84.5%** | **83%** | **94.5%** |

**Tab.IV.3:Recognition rates (%) obtained using LBP.**

In this part, we experimented with the face recognition method based on LBP descriptors. this experiment consisted of observing the recognition rates depending on the number of images present in the database and the different values of the torque (P, R) and compare the success percentage. This is to see the robustness of the method, that is to say if it also worked for particular cases.

### IV.4.3 Discussion

In this part, we first presented a face recognition system based on an approach which has had the most success in this field: PCA (Principal Component Analysis) known under the name “Eigen Face”, which is a quick, simple and popular technique in face identification. PCA projections are optimal for the reconstruction of a reduced dimension base. We tested the performance of this technique on the ORL database according to different galleries and numbers of Eigen faces where it turned out that the recognition rate is maximum using all of the Eigenfaces. The main choice of this database is its large size, and its popularity since it has become a standard in the biometric identity verification community.

In the second part the application of the technique ('local binary patterns') for face recognition converts images into local binary patterns, divides them into several sub-regions and determines the identity of a face by comparing their histograms of subregions.

The authentication method, based on an LBP representation of the image. It offers better robustness to light conditions and a simpler and faster training procedure.

Although holistic methods in this case the method of eigenfaces have been very successful, their major drawback is that they only use 2D photos of facial appearance. However, we know that such a representation is sensitive to changes in expression, illumination and poses. One way to avoid this problem is to use local facial representations. This is because local features are generally not as sensitive to appearance changes as global features.

The first notable point of these experiments is that learning PCA poses a generalization problem, found in all recognition methods by space reduction. Knowing that if the reduction space is constructed from people who are not in the ORL evaluation base, performance is significantly degraded. We also notice that the variability of people is less important than the variability of environmental situations. This technique also suffers from a large calculation time. Knowing that the evaluation of a recognition system is essentially done in relation to two parameters which are: robustness and execution time, it is not dedicated to real-time applications, and is not optimized for class separability (discrimination).

## IV.5 Principle of the recognition system

We can define our system and its role in two parts:

- Verification mode
- Identification mode

### IV.5.1 Verification mode

This mode consists of comparing an image to another stored in the database.

- Import an image from the test database.
- Import an image from the training database.
- Perform reconnaissance.

### IV.5.2 Identification mode

In this phase we compare an image with all the images in the training database.

- Import an image from the test database.
- Compare this image with those stored in the database

## IV.6 Presentation of the application

In this section we present the different aspects of our recognition system.

### IV.6.1 Project Presentation Interface

It is an interface intended for users, it is simple and allows to illustrate the main processes of the recognition system (identification, average face, image reconstruction, own face). These operations are carried out on the databases (ORL and FEI) described in this chapter.

- the first interface contains two buttons:
- **'Start':**to start the program.
- **'close':**to exit the program.

To start the program, click on the 'Start' button:

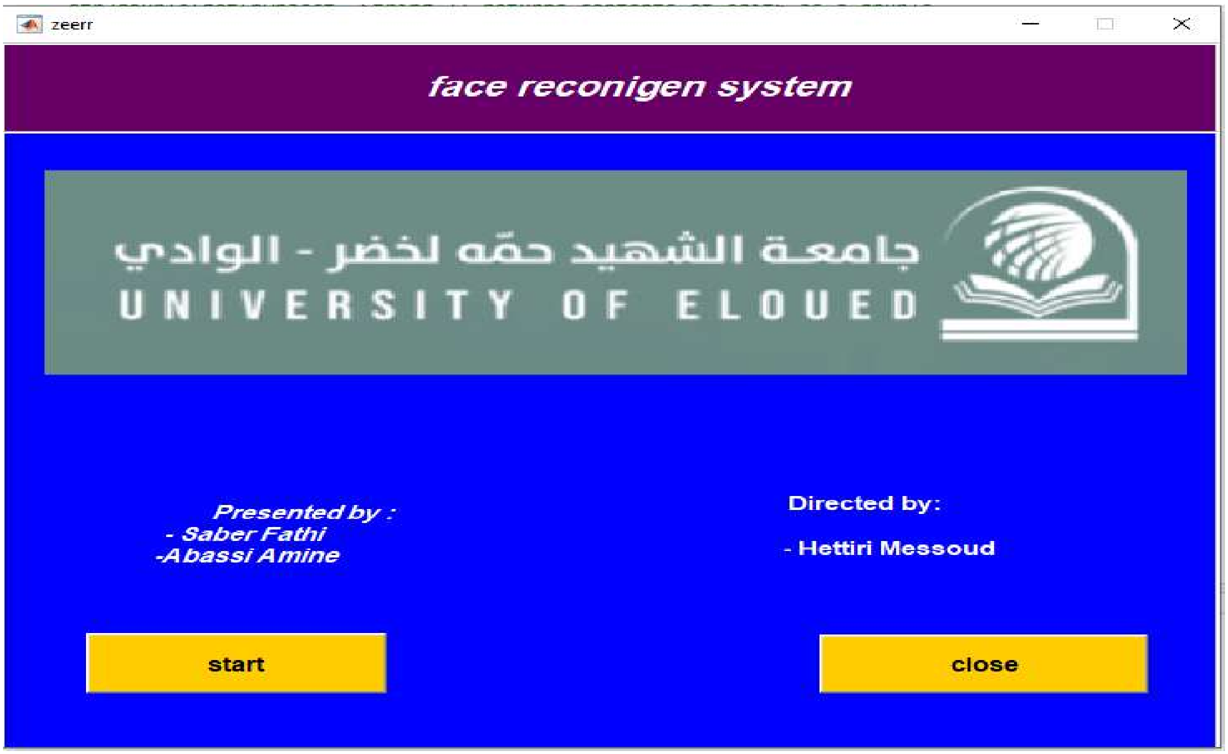


**Fig.IV.13:Graphical interface of our application**

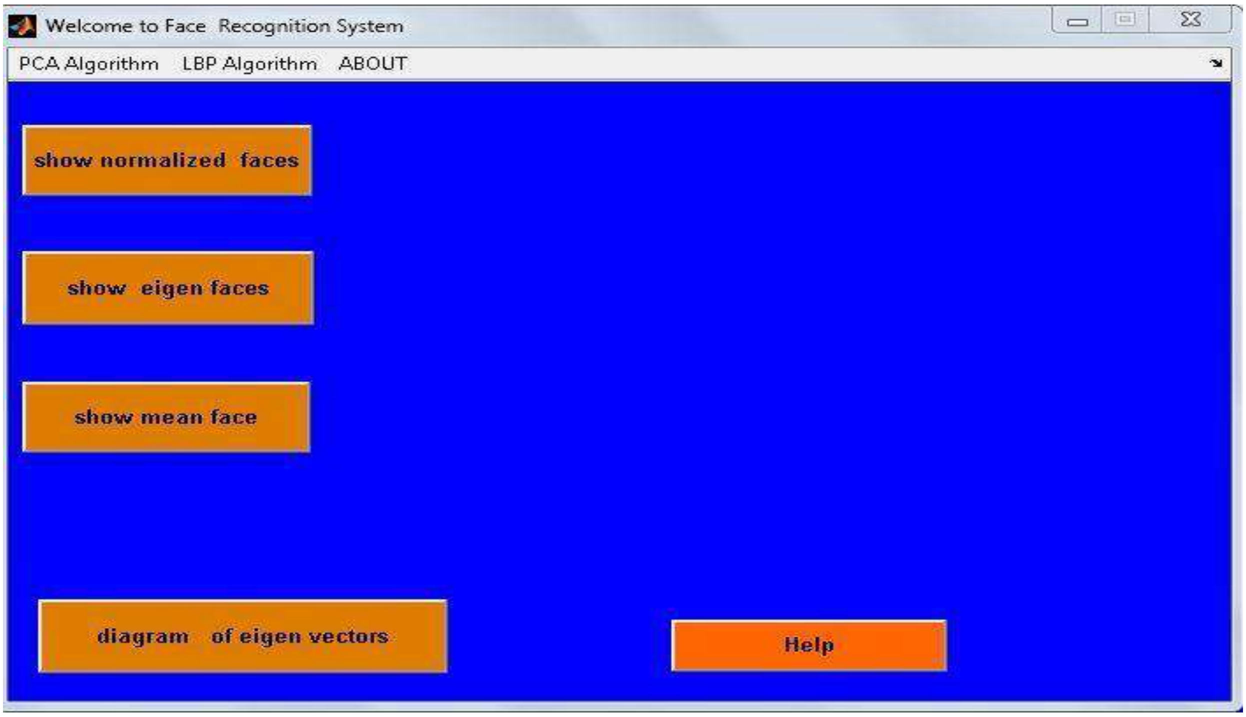


**Fig.IV.14:The facial recognition GUI.**

the 2th interface is built in three menus:

1. The PCA Algorithme interface (groups two menus where each menu represents two phases: ORL data base and FEI data base).
2. The LBP Algorithm interface. (groups two menus where each menu represents two phases: ORL data base and FEI data base).
3. The ABOUT interface presents an information guide to our system

**IV.6.2 The PCA interface Facial recognition algorithm** The PCA Algorithm interface contains 5 buttons and an axis for display:

A- **The "show normalized face" button** :the program displays faces normalizes in the axis.


**Fig.IV.15:standardized faces.**

B- **the "show mean face" button :**after normalizing the faces in the database our program calculates the average face then represents the latter in the display axis.


**Fig.IV.16: Mean image**

c- **The "show eigen faces" button:** In this case the program calculates the eigenvectors for each image and displays the eigenfaces in the axis.

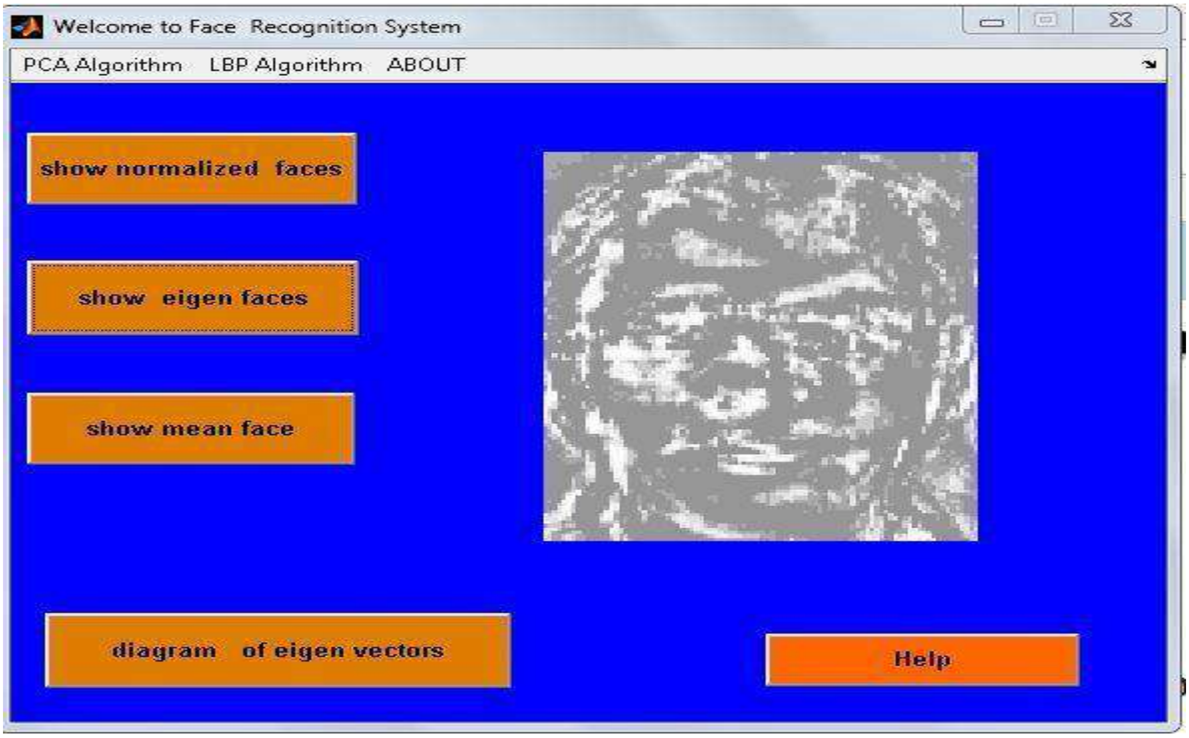


**Fig.IV.17:Eigenfaces.**

D- **the “diagram of eigen vectors” buttons :**gives the eigenvalue plotting diagram.

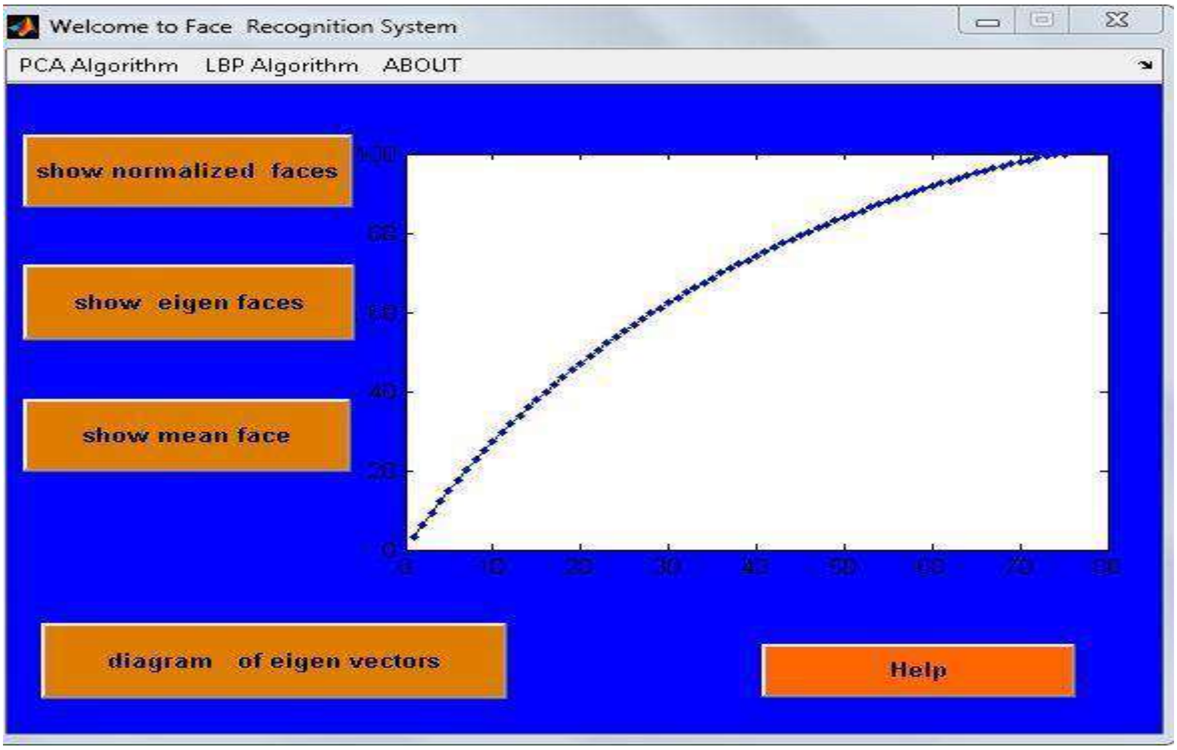


**Fig.IV.18:Plotting the diagram of the eigenvectors.**

E- **the “help” button :**gives more information about our application. To carry out the tests, choose the ACP or LBP technique from the menu. The test interface is shown in the following figure:

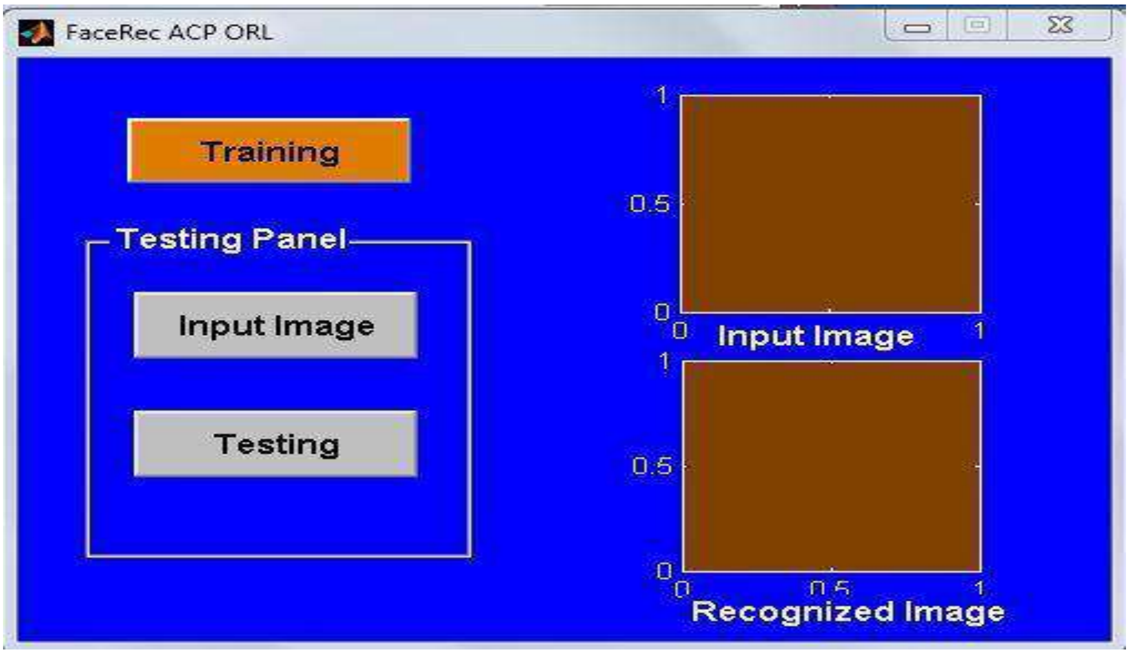


**Fig.IV.19:ACP test interface**.

### Test on the ORL base

We click on the training button: in this case the program creates and saves the projection matrix. When the program is finished we receive a message box.


**Fig.IV.20:end of training message.**

Then we select the input image button to enter the test image path.

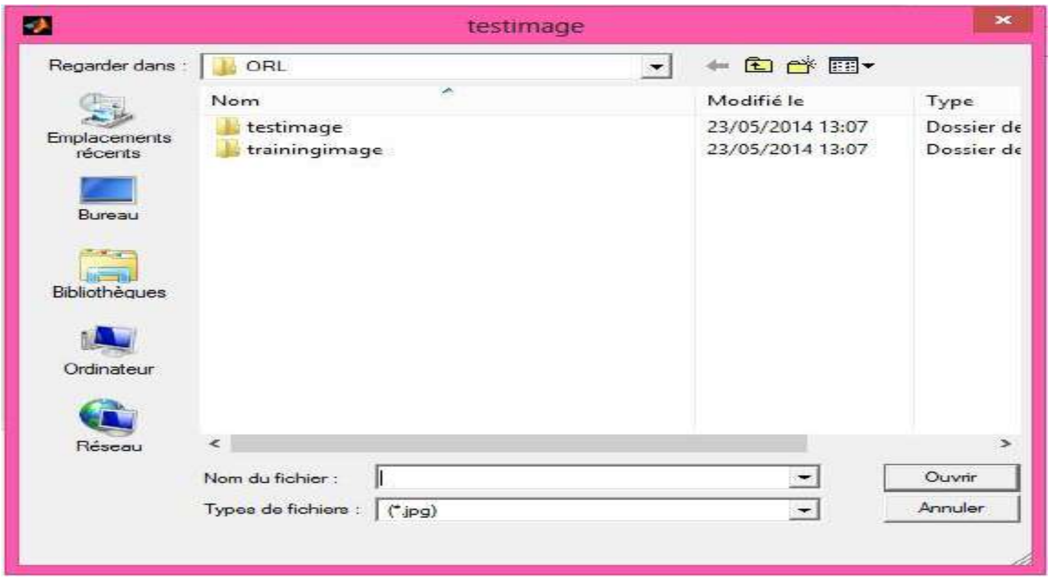


**Fig.IV.21:choice of test image path.**

After the testing button you can view the face recognized by the system.

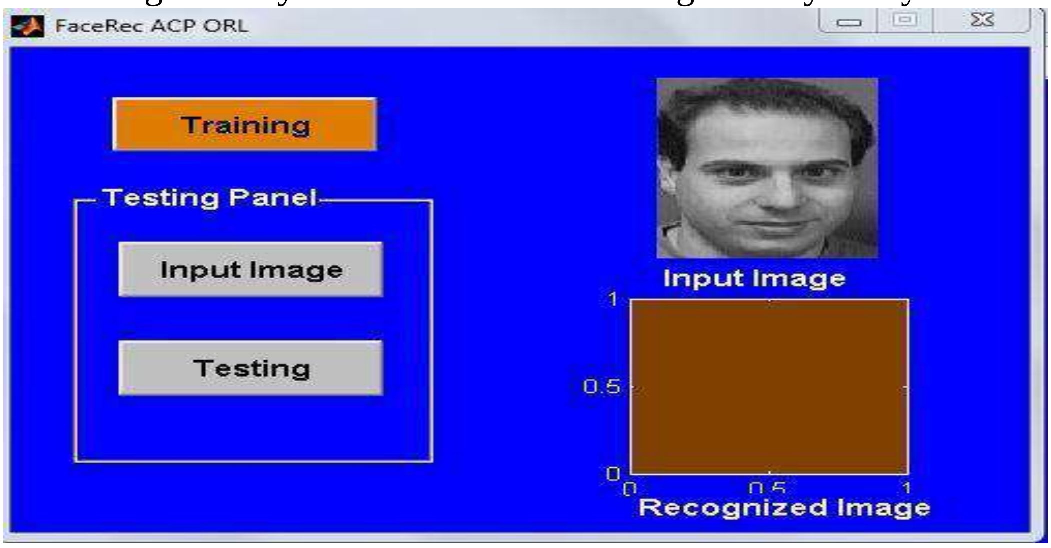


**Fig.IV.22:test image display.**

In this case the program is read and compared with the trainning images.

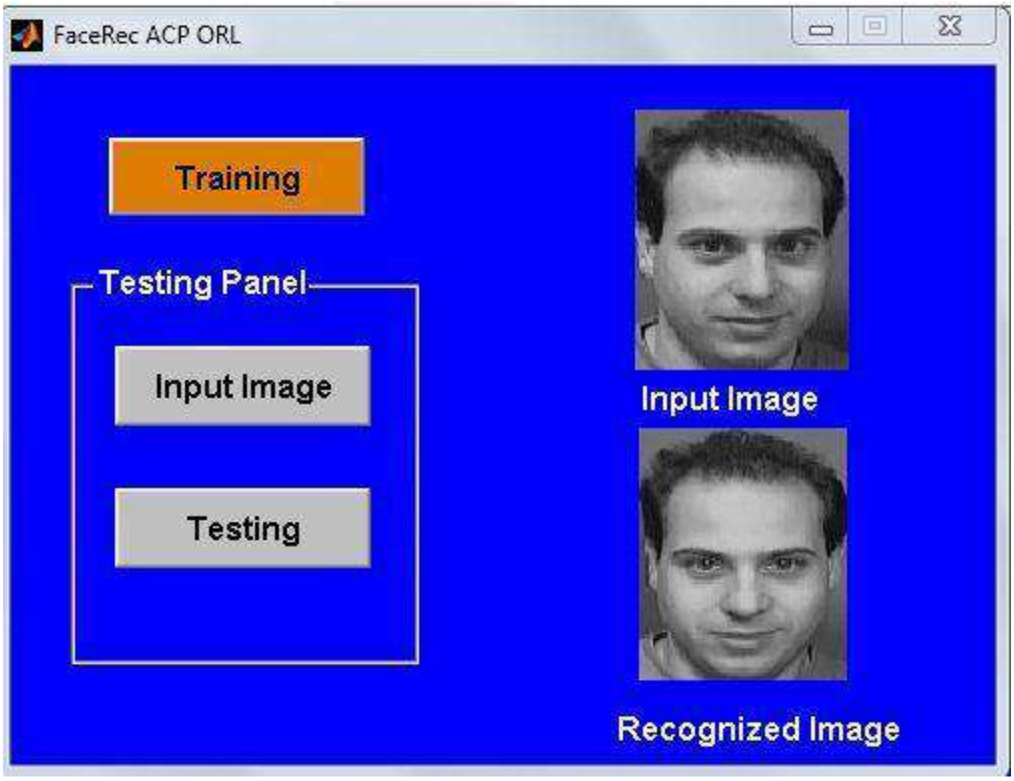


**Fig.IV.23:end of testing stage.**

### IV.6.3 Experiments

#### A. ORL basis

In this part the ACP algorithm is applied to the ORL base, the latter is split into two sub-bases, the first which is called “trainingimage” it is a learning base it contains 100 images. and the second is calls “testimage” it is a test base it contains 70 images. After execution:

- ✓ The number of test images that our system knows =64 images.
- ✓ The number of test images which our system unknown =6 images.
- ✓ The total number of test images =70.

**Recognition rate for the ORL database by PCA algorithm = 91.42%.**

#### B. FEI basis:

In this part the ACP algorithm is applied on the FEI basis which is separated as follows:

A sub-base called “traifei” (contains 114 images) for the learning base, another sub-base called “testfei” (contains 74 images) for the test base.

After execution:

- ✓ The number of test images that our system knows = 61 images.
- ✓ The number of test images which our system unknown = 14 images.
- ✓ The total number of test images =75.

**Recognition rate for the FEI base by ACP algorithm = % 81.33.**

### IV.6.4 The LBP Algorithm interface

In this interface the 'local binary pattern' technique is used for face recognition, we will choose the database to apply the test by the LBP algorithm in the LBP Algorithm menu.

If we choose LBP ORL then there is a new interface which is presented in the figure.

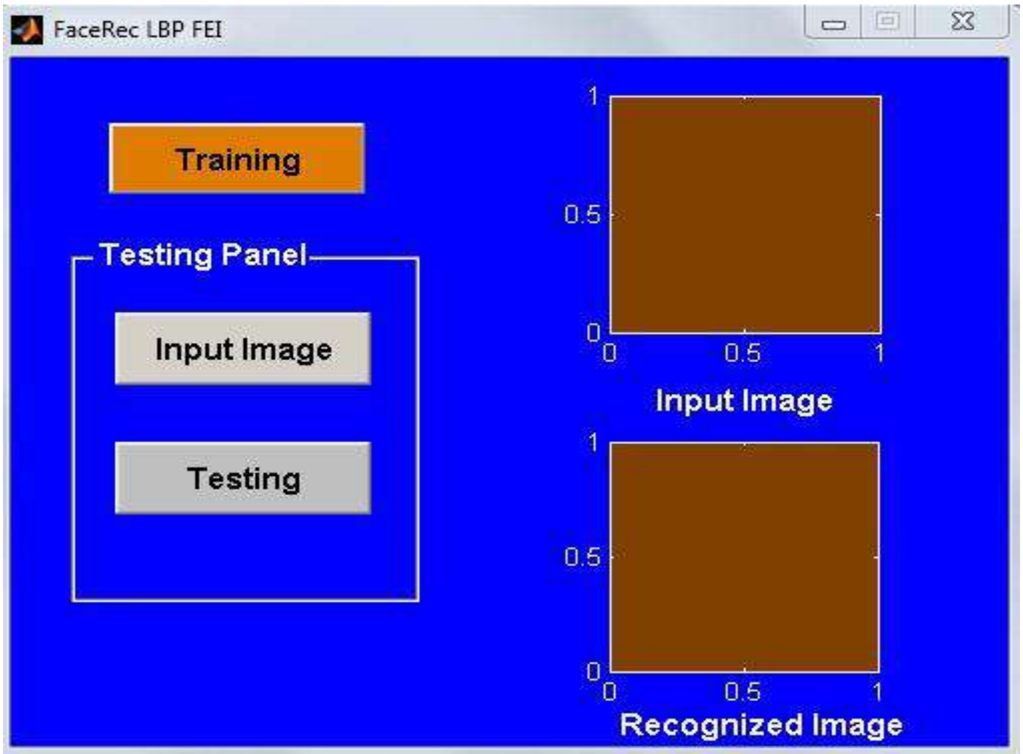


**Fig.IV.24:the test interface for LBP from the FEI database.**

1. Click on the training button

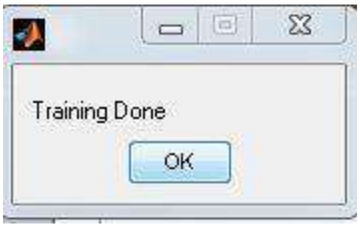


**Fig.IV.25:End of training message.**

2. Click on the input image button to select the test image

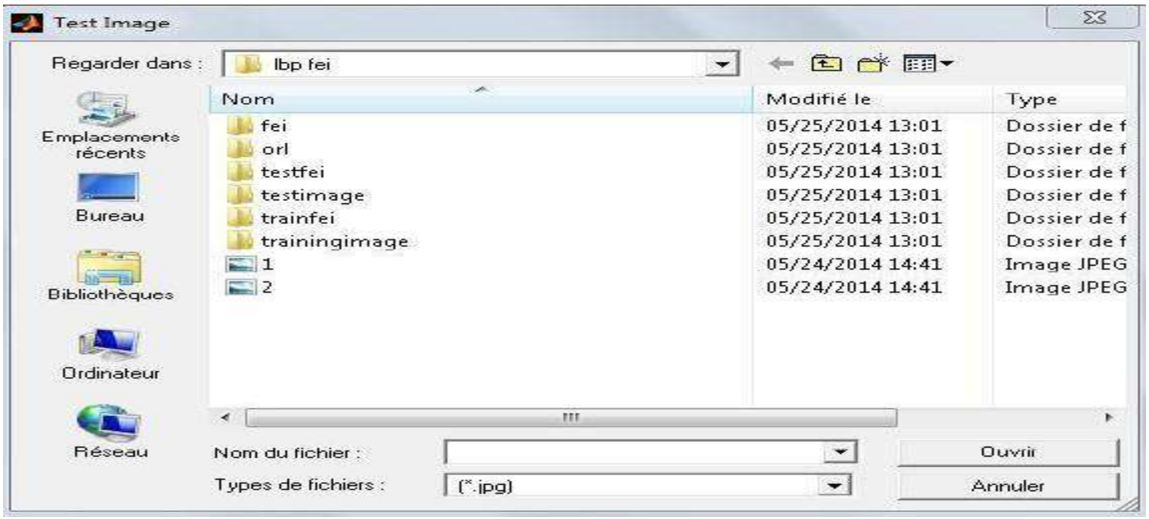


**Fig.IV.26:the choice of the test image for the FEI database.**

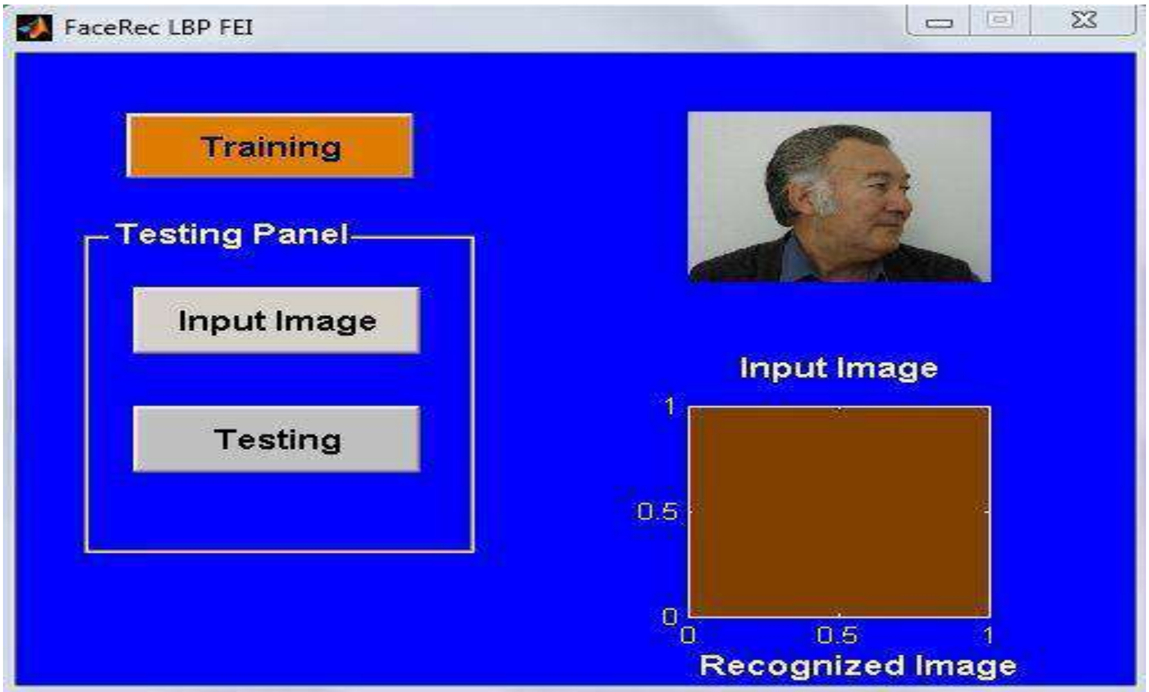


**Fig.IV.27:displaying the test image.**

3. We click on "testing" to identify the test image:

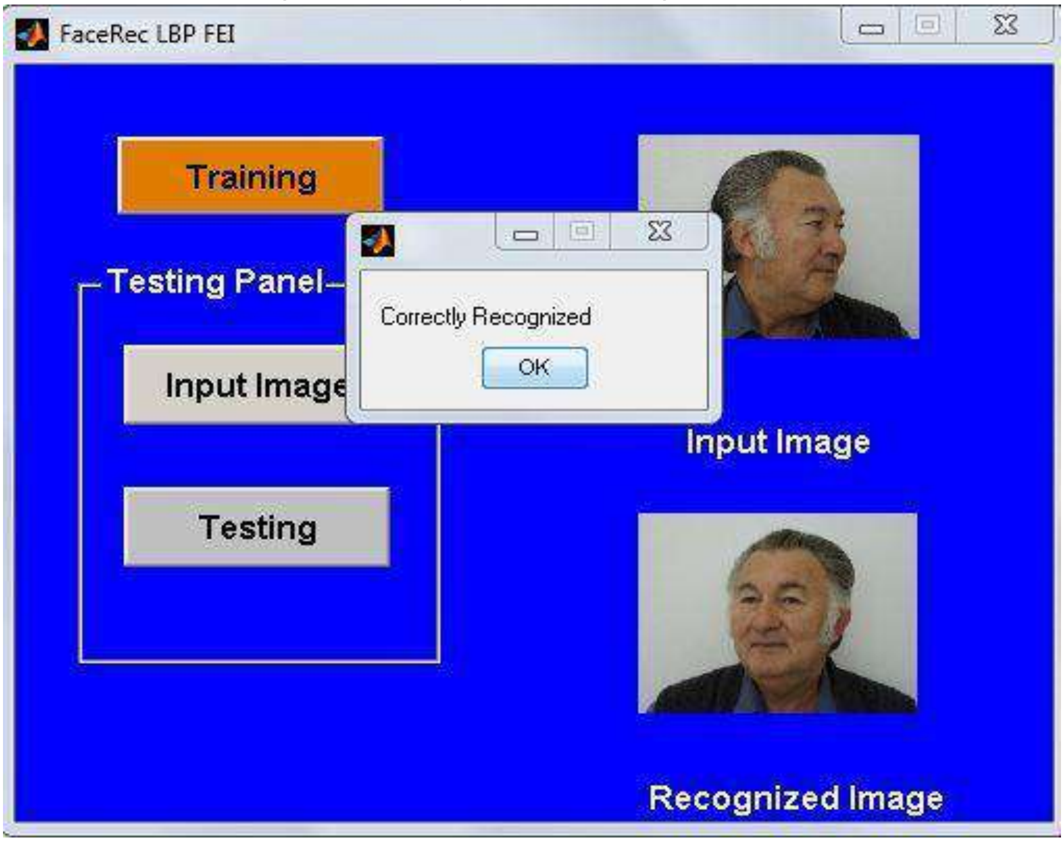


**Fig.IV.28:end of the test step.**

### IV.6.5 Results

**1) Recognition rate for the ORL database**

We applied the LBP algorithm to the ORL database, the latter contains 400 images of 40 different people. Each individual is represented by a set of 10 images, the first 6 images were selected for training and the remaining 4 for the different test.

- ✓ The total number of test images 40*4 =160.
- ✓ The number of images known by our program is 160.
- ✓ The number of images unknown by our program is zero. SO :

**Recognition rate for the** ORL **database by LBP algorithm = 97%.**

**2) Recognition rate for the FEI database:**

We applied the LBP algorithm on the FEI database which contains 10 images for each of the 21 individuals, for a total of 210 images.

- ✓ The total number of images equal to 21*10 = 210.
- ✓ The number of images known by our system is 200.
- ✓ The number of images unknown by our system is 10.

Then:

**Recognition rate for the FEI database by LBP algorithm = % 95.23**

## IV.7 Comparison table between algorithms

| | algorithm**ACP** | Algorithm**LBP** |
|---|---|---|
| Database **ORL** | **91.42%** | **97%** |
| Database**FEI** | **81.33%** | **95.23%** |

**Tab.IV.4:Comparison table between algorithms.**

## IV.8 Conclusions

In this chapter, we presented a facial recognition application based on the ACP and LBP algorithms, we also presented the different results obtained for each algorithm.

Our face recognition system, face recognition system, is applied to two databases of ORL and FEI faces. To conclude, We can note that Eigenface becomes slower and slower as the number of images in the database increases as well as experiments have shown that the LBP face recognition method is the most effective than PCA . However, we have also seen that many external factors influence the quality of recognition.

# General conclusion

Biometrics is a field that is both exciting and complex. It attempts, using often very advanced mathematical tools, to distinguish between individuals, forcing us to work in a context of great diversity. This diversity is also found in the considerable number of algorithms that have been proposed in facial recognition.

In this thesis, we are interested in the problem of facial recognition. Our work consists of the development of a robust algorithm intended to recognize an individual by their face using two methods among the most used methods in this field. The first technique is “Eigenface” which is based on a principal component analysis. (ACP). PCA is a mathematical method that can be used to simplify a data set, by reducing its dimension. It is used to efficiently represent face images, which can be approximately reconstructed from a small set of weights and a standard face image. The second technique used is LBP (local Binary Pattern), it is a mathematical method whose aim is to characterize the texture of an image by calculating the LBP code for all the image pixels then calculating the histogram of this LBP image to form a feature vector representing the facial image.

During this work, we highlighted the harmful influence on the recognition rate of the system and for this we proposed some solutions which were evaluated during the test phase. Despite all the progress that has been made, the problems of installation and lighting for identification in outdoor environments remain challenges that will spark the efforts of researchers. PCA remains an effective and simple method for managing this type of problem. It is for all these reasons that we opted for this face recognition approach.

We believe that we have created a system that meets the objective that we initially set for ourselves, namely the implementation of a system allowing the recognition of individuals and access control.

As a perspective, initially an extension of this work can be considered by the study and creation of a facial detection and localization system with fairly

high performances, another consists of applying this system on other bases of faces presenting strong variations in lighting and pose as well as to consider the possibility of employing an approach based on local elements of the face.
General conclusion.

Then, one of the major challenges would be to be able to better control environmental variations, which are still too disruptive to recognition systems. The latest advances in 3D facial image capture technology have made it possible to set up fairly specific recognition systems. robust compared to 2D.

If biometrics is an important issue at the economic level, research, particularly in the field of face recognition, still offers a very open field of investigation.

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# Résumé

Au cours de ces dernières années, on observe un intérêt croissant autour de la biométrie. La reconnaissance faciale en tant qu'une technologie biométriques de base, a pris une part de plus en plus importante dans le domaine de la recherche, du fait de son caractère non intrusif et sans contact. Mais malgré les nombreuses approches et méthodes qui ont été proposées pour résoudre le problème de reconnaissance du visage humains, il demeure un problème extrêmement difficile, ceci est dû au fait que le visage de personnes différentes ont généralement la même forme et varie du fait des conditions d'éclairage, de la variation de pose, et des expressions faciales. De nos jours les systèmes de vérification d'identité apparaît être un vecteur intéressant à exploiter, vu la multitude des applications qui leurs font appel contrôle d'accès aux sites sensibles, télésurveillance...etc.

Le travail effectué dans le cadre de ce mémoire porte sur l'identification automatique de visages avec deux méthodes de reconnaissance faciale en utilisant l'analyse en composantes principales (ACP) et local binnary pattern (LBP). Les résultats, obtenue ont montré que LBP donne nettement des meilleurs résultats par rapport à l'ACP .Pour validé ce travail nous avons testé ces techniques sur des images frontales de les bases de données ORL et FEI.



***Mots-clés:***

*Reconnaissance de visages, Biométrie, ACP, LBP, extraction de caractéristiques, eigenfaces.*



# ملخص

خلال السنوات الأخيرة , هناك اهتمام متزايد حول المقاييس الحيوية. وقد أخذ نظام التعرف على الوجه - كقاعدة التكنولوجيا الحيوية - أهمية متزايدة في مجال البحوث ، بسبب عدم التدخل والتماس. لكن على الرغم من الكثير من النهج والأساليب التي تم اقتراحها لحل المشاكل المتعلقة بالتعرف على الوجه البشري، فإنها لا تزال مشاكل صعبة للغاية، وهذا يرجع إلى حقيقة أن الناس على اختلافهم يمتلكون عموما نفس الشكل ويختلف بسبب ظروف الإضاءة، واختلاف الوضعيات، وتعابير الوجه. في الوقت الحاضر تعتبر نظم التحقق من الهوية مجالا هاما لاستغلال، و هذا بالنظر إلى العديد من التطبيقات التي تستخدم فيها لتحكم في الوصول إلى المواقع الحساسة، والرصد عن بعد ... الخ.

يركز العمل الذي نقوم به كجزء من هذه الأطروحة على تحديد وجه التلقائي مع أسلوب "مختلط" للتعرف علي وجه بإستخدام طريقتين للتعرف على الوجه وهما تحليل المكون الرئيسي(آسيبي) و النموذج الثنائي المحلي (ال بي بي) .النتيجة المحصل عليها تبين أن ال بي بي تعطي أفضل نتيجة مقارنة ب الآسيبي. لللتحقق من صحة هذا العمل قمنا بإختبار هاتين التقنيتين على الصور من قاعدة البيانات "أو آرآل"و"اف او اي".



**كلمات البحث:**

التعرف على الوجوه، القياسات الحيوية،تحليل المكونات الأساسية، النموذج الثنائي المحلي ، استخراج الخصائص ، القيم الفردية.



# Abstract

In recent years, there has been a growing interest around biometrics. Facial recognition, as a biometric technology, has played an increasingly important role in the field of research, because of its non-intrusive and contactless. However, despite of the many approaches and methods that have been proposed to solve the problem of human face recognition, it remains an extremely difficult problem. this is due to the fact that different people faces have generally the same shape and vary due to the lighting conditions , variation of pose , and facial expressions. Nowadays, identity verification systems appears to be an interesting domain to exploit, given the multitude of applications that utilize their controlling access to sensitive sites, remote monitoring ... etc.

The work done as part of this thesis is focused on identifying automatic face with two methods for face recognition principal component analysis(PCA) and local binary pattern(LBP). The results, of LBP compared with the PCA, provide a significant improvement in performance. For the validation of this work, we tested this technique on frontal images of the database ORL and FEI .



***Keywords:***

*Face recognition, Biometrics, PCA,LBP , feature extraction, eigenfaces.*